APPROACHES FOR THE DEVELOPMENT OF EARLY-STAGE ENGINEERING DESIGN SKILLS

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APPROACHES FOR THE DEVELOPMENT OF EARLY-STAGE ENGINEERING DESIGN SKILLS

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LIST OF SYMBOLS AND ABBREVIATIONS

1^{st} Gen	First-generation college student
CAD Software	Computer-Aided Design Software
EDSE	Engineering Design Self-Efficacy
ED	Engineering Design
EDP	Engineering Design Process
GD&T	Geometric Dimensioning and Tolerencing
MRT	Mental Rotations Test
PSVT:R	Purdue Spatial Visualization Test on Rotations
URM	Under-Represented Minority

SUMMARY

Early-stage engineering design skills are crucial for the generation and development of solutions to the problems faced by engineers today. Avenues for engineers to develop these critical skills need to be identified and these skills need to be infused into the already packed engineering curriculum. The following work is presented in two studies which aim to develop these key skills. The first study investigates the impacts made on mechanical engineering students who are taught industrial design-based freehand drawing techniques during a six-week, introduction to engineering graphics course. Freehand sketching is an essential skill for communication and visualization in engineering design. The study compares two pedagogies for teaching engineers to sketch: Traditional and Perspective. The Traditional pedagogy contains concepts that have been commonly found in engineering graphics courses. The Perspective version of the course is based on a pedagogy from an industrial design course and contains concepts generally regarded as more advanced sketching skills. The Perspective approach was expected to provide greater free-hand sketch ability and sketching confidence, but its impact on spatial visualization was also explored. Pre- and post-course evaluations measured design self-efficacy and spatial visualization using the Revised Purdue Spatial Visualization Test on Rotations (PSVT:R) and the Mental Rotation Test (MRT). Both sketching approaches improve MRT scores, but there were no significant differences between the groups. For initially low scoring students, similar trends are observed as when comparing the full sample size. Sketching ability is also measured in both courses, with the Perspective method found to be significantly more likely to improve student sketching ability. Thus, the Perspective

method was found to be as effective as the Traditional approach for developing spatial visualization skills while developing additional free-hand sketching skills.

The second study investigates the impacts of gaining additional prototyping experience through involvement in a makerspace through a longitudinal study of engineering students at three universities. University makerspaces have been touted as a possible avenue for improving student learning, engagement, retention, and creativity. As their popularity has increased worldwide, so has the amount of research investigating their establishment, management, and uses. However, there have been very few studies that use empirical data to evaluate how these spaces are impacting the people using them. This study of three university makerspaces measures engineering design self-efficacy and how it is correlated with involvement in the makerspaces, along with student demographics. The three university makerspaces include a relatively new makerspace at a Hispanic-serving university in the southwestern US, makerspaces at an eastern liberal arts university with an engineering program that has been created within the last decade, and a makerspace at a large, research university in the southeast. Students at all three universities are surveyed to determine their involvement in their university's makerspace and how they perceive their own abilities in engineering design. The findings presented in this paper show a positive correlation between engineering design self-efficacy and involvement in academic makerspaces. Furthermore, correlations are also seen between certain demographic factors and the percentage of students who choose to use the academic makerspace available to them. These findings provide crucial empirical evidence to the community on the self-efficacy of students who use makerspaces and provide support for universities to continue making these spaces available to their students. The impacts of involvement in academic makerspaces was also investigate, but no statistically significant results were found.

Together, these studies provide two avenues through which engineers can develop key early-stage engineering design skills such as free-hand sketching and early-stage prototyping. This provides engineering educators with additional tools and resources for how students can be better developed as engineering designers while maintaining the rest of the curriculum.

CHAPTER 1. INTRODUCTION

The work presented in this dissertation is divided into two main studies. The first study explores the impacts of teaching freehand sketching to students in a freshman-level engineering graphics course. This includes observations of teaching sketching via two different pedagogies in a course where students also learn to use a computer-aided design (CAD) software. The second study is a multi-university study into the impacts of involvement in an academic makerspace. This study primarily seeks to determine how students who are involved in an academic makerspace are impacted in areas such as engineering design self-efficacy.

1.1 Study 1: Effectively Teaching Sketching in Engineering Curricula

The ability to generate visual representations is essential for engineering design (Pleck 1991, Yang 2004, Dym, Agogino et al. 2005, Goldschmidt 2007, Booth, Taborda et al. 2016), and as CAD programs have been developed, it has become easier to develop a computer-generated rendering of a design. However, CAD has been found to be hindering in the design process if used too soon or too often, as it leads to fixation (Yang 2004). A better practice is to use hand-drawn sketches during idea generation and development phase (Goldschmidt 1991, Yang 2003). Other benefits of sketching involve improved collaboration (Shah, Vargas-Hernandez et al. 2001), improved conceptual understanding (Gobert and Clement 1999), and improved understanding of ill-defined problems (Cross and Roy 1989). How well a design is sketched can also influence how creative the design ideas are perceived (Kudrowitz, Te et al. 2012). Finally, sketching three-dimensional objects has been found to improve spatial visualization ability (Olkun 2003, Sorby 2009).

Despite the many benefits of teaching free-hand sketching to engineers, it is not widely taught in the engineering curriculum (Ullman, Wood et al. 1990). This study presents two methods of teaching sketching in engineering and the presented curricula can create more effective engineers.

Traditionally, sketching in the engineering curriculum is taught with the purpose of providing dimensions for a product to be created in the form of drafting engineering drawings and simple isometric and sectional views (Pucha and Utschig 2012). As CAD has become more prevalent in Engineering Design courses, these types of sketches feed directly into CAD drawings. The inclusion of this type of sketching has been shown to improve skills such as spatial visualization, but otherwise, gives the students the same benefits as using CAD alone. The hypothesis of this paper is that the ability to generate more realistic sketches of objects can further improve spatial recognition while also improving sketching ability more than the traditional engineering approach. Courses in the industrial design curricula have developed pedagogy to train designers in sketching through the use of elements such as perspective view, shading, and ray tracing. According to The Engineer of 2020: Visions of Engineering in the New Century (National Academy of Engineering 2004), the engineering profession must leverage innovative developments of non-engineering fields, and this still has not been accomplished. Therefore, in recent years, instructors in mechanical engineering have partnered with instructors from industrial design to develop a suitable curriculum to replace the sketching-based portion of a freshman-level engineering graphics course. This method of teaching perspective sketching has been introduced in engineering curricula to allow engineering students to gain some of the same benefits from sketching instruction in industrial design education.

1.1.1 Traditional Method

Introduction to Engineering Graphics and Visualization is a freshman-level cornerstone design course in the mechanical engineering department at a public research university with the goal of teaching students to develop and interpret engineering drawings and representations. The first five weeks of the course is dedicated to drawing and the remaining 10 weeks are dedicated to solid modeling using CAD software. In the Traditional version of this class, the sketching portion of the course is primarily focused on developing engineering drawings such as those developed for manufacturing purposes. Two-dimensional and three-dimensional drawings are created, but three-dimensional drawings are only isometric. Almost all of the drawings are done using grid paper and straight-edge tools. Figure 1 shows an example shown in class on how to generate an isometric drawing of a complex shape. Note the use of a straight edge and graph paper. In general, the drawings in the class are intended to prepare the students to create computer-generated solid models in the latter portion of the course.

1.1.2 Perspective Method

In recent years, professors in the mechanical engineering department have worked with professors from the industrial design department to implement the method of teaching sketching used in industrial design to the sketching portion of the Introduction to Engineering Graphics course in mechanical engineering. This method of the class includes teaching techniques such as thumb-nailing (Figure 2a), perspective (2b&c), primitives, drawing complex shapes in perspective, shading (2b&c), and ray-tracing to create shadows that mimic a light source (2c). Figure 2 shows a series of student work from assignments given throughout the first five weeks including a) thumb-nailing a dorm room object, b) drawing primitive basic shapes in perspective using shading to show surface texture, surface texture, and c) sketching a concept for a product. All of the assignments are presented during the lab session in a gallery style showcase where all of the students can walk around and see everyone's sketches and provided critiques and praise to their classmates. This method of the course focuses more on developing the ability to generate realistic renderings of objects and or idea using only sketching.

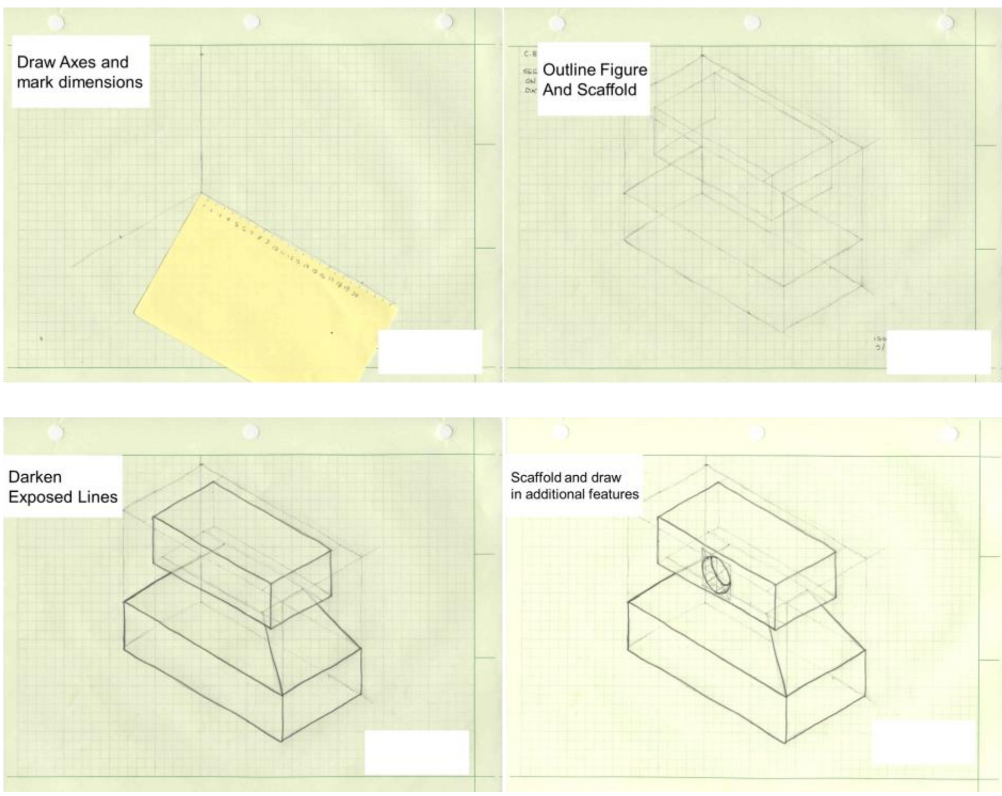
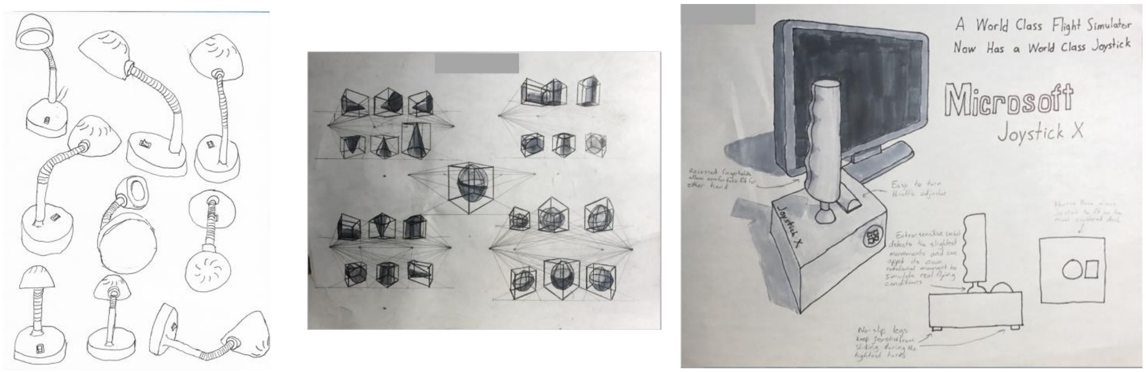


Figure 1. Example from Traditional version of the course on how to draw an object in isometric view.



a) b) c)

Figure 2. Example of student work from Perspective method course: a) thumbnails of a dorm room object, b) exercise of multiple 3D shapes in perspective, c) concept product sketching in perspective with appropriate shadows

1.1.3 CAD Portion of the Course.

The remaining twelve weeks of the semester are dedicated to learning solid modeling techniques via computer-aided modeling software. The lectures during this part of the course focus on how to represent product ideas. This included lessons on topics such as geometric dimensioning and tolerancing (GD&T) and creating auxiliary views of models. The lab works as a flipped class, with the students watching online modules to learn how to navigate and use a CAD program outside of class time while the lab is dedicated to completing a lab assignment with TA and professor feedback. Both versions of the course share nearly identical lectures for the CAD portion of the course.

While the introduction to engineering graphics course was not developed with the primary goal of improving spatial visualization skills, literature supports that the practice of generating representations of three-dimensional objects in isometric views improves these skills (Sorby 2009).

1.2 Study 2: Impacts of Involvement in an Academic Makerspace

Around the world, universities are opening makerspaces on their campuses with the hopes that these spaces will foster student retention, engagement, learning, and creativity, especially for engineering students (Forest, Moore et al. 2014, Wilczynski, O'Hern et al. 2014, Barrett, Pizzico et al. 2015, George-Williams 2015, Blacklock and Claussen 2016, Weinmann, Farzaneh et al. 2016, Wilczynski, Wigner et al. 2017). Though there are many reports published on budding makerspaces, few include empirical data-driven studies (Rosenbaum and Hartmann 2017, Weiner, Lande et al. 2018). We seek to begin to remedy this gap. In this study, measures of engineering design self-efficacy, involvement in makerspaces, and demographics were collected from students from three universities. The construct of engineering design self-efficacy was used as a way to measure participants' self-concept and confidence in engaging in the design process. Bandura (1977) defines self-efficacy as an individual's belief in their own ability to complete a task, and his research correlates self-efficacy with effectiveness and success. Further, the literature shows that students with high levels of engineering-related self-efficacy tend to be more engaged in their communities of learning and more likely to persist within their engineering major (Concannon and Barrow 2009, Marra, Rodgers et al. 2009, Concannon and Barrow 2010, Jordan, Amato-Henderson et al. 2011, Hsieh, Sullivan et al. 2012, Marra, Rodgers et al. 2012, Mamaril, Usher et al. 2016).

1.2.1 Spaces Studied

Data were collected from students at three universities through surveys. These data were collected in the spring and fall semesters of 2016. University A is a Hispanic-serving public research university in the US southwest. University A opened its first university-wide makerspace in the spring of 2016. This 600-sq. ft. space is housed within a faculty-supported STEM education and research institute and is physically located in an academic services building. Within the building, the makerspace overlooks the university writing center, which is frequented by students from all majors. This location is geographically closer to the College of Education than to the College of Science and Engineering. The makerspace is staffed by student volunteers, modeled upon University C's makerspace staffing, where volunteers are given door card access to the makerspace in exchange for 3 hours per week of staffing the space. The students have tremendous ownership of the space, and they have created a social media account and promotional video for the space. The volunteer staff offer training in the equipment and design software to students who come to use the makerspace. The student staff began with around 3-5 volunteers (at the time of data collection) and the staff have been steadily growing over the first three years of operation to 10-15 volunteers. There are two faculty members who co-direct the space. The cross-disciplinary nature of this makerspace is reflected by the co-directors' home departments: Curriculum and Instruction (College of Education) and Engineering Technology (College of Science and Engineering). The co-directors offer mentoring and training to the student volunteers as well as conducting research and grant administration on and for the makerspace. Equipment available in the space includes 3D printers, sewing machines, an embroidery machine, a laser engraver/cutter, a desktop CNC mill, a digital vinyl and paper cutter, and a heat press. This makerspace is available to students in all majors. While some students come to the space for class projects, many of the users are working on personal projects.

University B is a public research university in the Atlantic coastal region. The university is historically known for its liberal arts programs but has offered degrees in engineering degrees since 2008. University B integrates design and making throughout the engineering curriculum. Students engage in the makerspaces through required curricular course experiences during their first two years and more optionally during their later two years due based on personal interests and capstone requirements. All students are trained during their first year to use the tools in fabrication studio through building a catapult with the shop management team; tools available include: power and manual hand tools, horizontal band-saw, table saw, panel saw, CNC router, and drill press. Following completion of the catapult, students can complete optional welding training in the fabrication studio. Reinforcement of fabrication skills occurs through design-build first-year projects such as building musical instruments for local children with disabilities. Sophomore year, students learn the engineering design process through a year-long design project which involves building a human-powered vehicle for a community member with a disability, and as a part of these courses students complete mill and lathe training in the machining studio. Completion of mill and lathe training allows students to apply to join the optional apprentice program run through the machining studio; student apprentices gain additional mill and lathe training through mentored use of machining equipment completing jobs for the university and engineering capstone class projects. Students join their two-year capstone projects as juniors, and many capstone projects require the use of the making spaces. All first-year, sophomore, and capstone students have studio space (with mobile furniture, whiteboards, and projection systems) dedicated to the academic year in addition to the making spaces.

Beyond the curricular making spaces, students at University B have access to a low fidelity prototyping studio, an ideation studio, a digital communication studio, and a make studio. The low fidelity prototyping studio includes such as pipe cleaners, tongue depressors, cardboard and foam board, and craft knives, and is designed to reinforce the idea of communication through prototypes taught during the first two years in the program. The ideation studio includes large tables, supplies for brainstorming activities, and a large floor-to-ceiling writable glass wall. The digital communication studio contains six pods, each with a large monitor for sharing designs and communicating ideas within small design teams. While these former spaces are designed to complement the design process education of University B students, the maker studio is meant to complement the fabrication studio and machining studio. The make studio contains 3D printers, a laser cutter, a vinyl cutter, 3D scanners, soldering station, and CAD stations.

University C is a public research university in the US southeast with globally recognized engineering programs. The largest makerspace at University C, at the time of the study, is housed in the school of mechanical engineering but is open to all of campus. The space is run primarily by students who volunteer their time. In exchange for 3 hours per week of leading other students in the use of the space, the volunteers are given 24/7 access. In this way, the students are encouraged to feel a sense of ownership for the space and its upkeep. There are typically close to 70 student volunteers at any time compared to only 5 faculty and staff leaders. The day-to-day operation of the space is handled almost entirely by the students, as the non-student leaders mainly focus on performing complex equipment repairs, ordering supplies, mentoring the student leaders and obtaining funding for the space. At the time of this study, the mechanical engineering makerspace consisted of 2500 sq. ft. of space with $600K of prototyping equipment. Funding has come from students' technology fee-funded proposals along with over 30 industrial sponsors through capstone design projects. Use of the space includes personal projects and required course projects, including a small project for a freshman engineering graphics course and a semester-long sophomore design course. Students also use the equipment in the makerspace for their senior capstone projects.

1.3 Research Questions

1.3.1 Research Questions Based on Sketching Research

In an attempt to determine the efficacy of teaching sketching in engineering curricula, a study was conducted to answer the following research questions:

RQ.1) What are the impacts of teaching engineers sketching via an industrial design-based pedagogy?

RQ.1.1) Can a 6-week course in freehand sketching measurably improve engineers' free-hand sketching ability?

RQ.1.2) Does an industrial design pedagogy for learning free-hand sketching improve spatial visualization as effectively as more traditional engineering drawing pedagogy?

RQ.1.3) How are spatial visualization skills impacted during a freshman-level course on sketching and computer-aided modeling?

1.3.2 Research Questions Based on Makerspace Research

In an effort to discover if makerspaces provide environments that build the self-efficacy of students in an engineering program, this study was conducted to answer the following research questions:

RQ.2) Makerspaces provide opportunities to increase the amount of prototyping experiences, how do these spaces impact students?

RQ.2.1) Does makerspace involvement improve engineering design self-efficacy?

RQ.2.2) How is makerspace involvement correlated to GPA?

RQ.2.3) Does makerspace involvement affect retention in engineering programs?

RQ.2.4) What factors influence students to become involved in an academic makerspace?

RQ.2.5) How consistent are the findings on impacts of makerspaces across three universities?

RQ.2.6) Are the impacts different for women, under-represented minorities, and first-generation college students?

CHAPTER 2. REVIEW OF PREVIOUS LITERATURE

This chapter presents relevant previous works on the importance of developing sketching and skills gained through participation in an academic makerspace.

2.1 Previous Literature on Developing the Sketching Skills of Engineering Designers

Sketching has been repeatedly shown to be a crucial skill in engineering design. It improves the communication abilities between design teams (Shah, Vargas-Hernandez et al. 2001) and improves idea generation (Linsey and Becker 2011). Perhaps the most impactful benefit of sketching is its ability to improve spatial visualization skills (Sorby 2009). Improving spatial skills has been correlated to success in engineering programs and increases retention (Pleck 1991).

With this knowledge, it is concerning that sketching is being taught less in engineering curricula as it is replaced by CAD programs (Ullman, Wood et al. 1990). In an effort to show more evidence in favor of including sketching in engineering curricula, this paper presents a study evaluating the spatial visualization skills of students as the progress through an introductory engineering graphics course that includes instruction in both sketching and the use of a CAD software to determine which portion of the course has a stronger impact on spatial visualization. Two different versions of teaching sketching are evaluated.

2.1.1 Sketching in Engineering Design

Dym, et al. (2005) call sketching one of the languages of engineering design and state that true design thought does not begin until a designer begins to sketch their ideas. However, as CAD programs have become more prevalent, there has been an increase in the amount of CAD instruction and a decline in engineering programs that teach sketching techniques to its students (Ullman, Wood et al. 1990). This is in spite of the fact that using CAD early in the design process is much more time consuming than generating quick sketches by hand, which could lead to fixation due to the higher sunk cost (Viswanathan and Linsey 2013). In fact, Yang (2004) has observed using CAD programs early on in the design process may in fact lead to design fixation. In another study, Yang (2003) found that sketching allows for a higher number of ideas to be generated and correlates to design outcome.

Sketching has also been found to be beneficial in a myriad of other ways for engineering design (Booth, Taborda et al. 2016). Kudrowitz, Te, and Wallace (2012) found the quality of a sketch has been linked to how well the idea represented by that sketch is perceived by stakeholders, which could both positively and negatively impact the final design outcome. Sketching also improves collaboration between multiple designers as it establishes a shared mental model for each design iteration (Shah, Vargas-Hernandez et al. 2001).

There have also been numerous studies on how using free-hand sketches can improve design problem understanding. Cross and Roy (1989) argue sketching as a technique to improve understanding of ill-defined problems. Similarly, Gobert and

Clement (1999) found that students who sketched difficult concepts in science classes created a more thorough conceptual understanding of the topic.

Perhaps one of the greatest arguments for including sketching in engineering curricula is the evidence that it improves spatial visualization skills (McKim 1980, Bowers and Evans 1990, Olkun 2003). In fact, Sorby (2009) adamantly states that sketching three-dimensional objects is the best way to improve spatial visualization skills. All of this is significant as spatial visualization skills have been found to be a key skill for students in engineering curricula.

2.1.2 The Importance of Spatial Visualization

Visualization abilities are considered crucial for engineering design (Pleck 1991). These skills are believed to be a strong factor in being able to successfully using computer-based technology as it allows users to see beyond what is presented on a screen. Ferguson (1994) even credits some of the success of the earliest engineers (da Vinci, Agricola, di Giorgio) with the fact that they began as artists and thus had more fully developed spatial visualization skills. More recently, extensive work has been done at Michigan Technological University (Sorby 2009, Sorby and Veurink 2010, Sorby, Casey et al. 2013) that has shown a correlation between spatial visualization skills and performance in engineering curricula. These correlations have driven decisions to create a first-quarter course for incoming freshmen with low spatial visualization skills designed to improve these abilities before beginning more advanced engineering coursework at MTU (Sorby and Baartmans 2000). This course has been found to greatly improve spatial visualization skills for its students and may increase retention rates in engineering majors, especially for women. The success of this course has begun to inspire other universities to develop similar courses (Walton, Urban-Lurain et al. 2015).

2.2 Previous Literature on the Impacts of being Involved in an Academic Makerspace

The formation of makerspaces has been growing in popularity throughout the United States in recent years. Lou and Peek (2016) reported that there were approximately 1,400 makerspaces worldwide in 2016, which is 14-times more than there were in 2006. *The Maker City* project reports that over 77 colleges and universities have pledged to implement or expand their own campus makerspaces (http://www.nationofmakers.us). *The MakeSchools Higher Education Maker Alliance* (http://make.xsead.cmu.edu), features 49 institutions with details of their makerspaces (e.g., locations, collaborations amongst departments, logistics, tools/equipment), who their makers are (e.g., faculty and students), and projects they have made (e.g., connections to coursework and extracurricular projects). Though there is not a clear definition of makerspace, Barrett et al. (2015) reviewed 40 university makerspaces and reported that the majority of university makerspaces are housed in colleges of engineering. However, many spaces provide access to non-engineering students, and they include a variety of equipment, such as 3D printers, laser cutters, wood shops, metal shops, electronics, and textiles.

Thomas and Besser (2017) state, “there is no authoritative body determining what is or is not ‘making,’ and who is or is not a maker. Makers self-identify and ...the inclusive nature of the term means that there are innumerable opportunities for inter-/cross-/anti-disciplinary work” (p. 33). Makers within a university makerspace community—regardless if they are majoring in engineering or a non-engineering discipline—can utilize the space to engage with like-minded individuals, and engage in design for personal enjoyment, or for a course-related project. Martin identifies three elements of the Maker Movement that are essential to consider in determining potential possible affordances for education: 1) digital tools, including rapid prototyping tools and low-cost microcontroller platforms, that characterize many making projects; 2) community infrastructure, including online resources and in-person spaces and events; and 3) the maker mindset, aesthetic principles, a failure-positive approach, collaboration and habits of mind that are commonplace within the community (Myers 2015).

Many approaches for improving engineering idea generation and innovation have been already identified (Linsey, Tseng et al. 2010, Linsey, Clauss et al. 2011, Viswanathan and Linsey 2012, Viswanathan and Linsey 2013, Viswanathan and Linsey 2013). Activities performed in a makerspace may also be akin to hands-on experiences gained through internships, which has been shown to improve students understanding of design documentation (Bailey 2007). Makerspaces likely improve idea generation and innovation through students learning about other designs and then applying this during design-by-analogy, which has been shown to enhance idea generation (Chan, Fu et al. 2011, Linsey, Markman et al. 2012, Fu, Chan et al. 2013) and multiple approaches along with tools have been developed (Fu, Cagan et al. 2013, Lucero, Viswanathan et al. 2014, Murphy, Fu et al. 2014, Tsenn, Linsey et al. in review). Learning to fail is another cited benefit of makerspaces (Wilczynski and Adrezin 2016). Consistent with this, experimental evidence suggests that when students build and test physical models, often failing, they can overcome design fixation and enhance their mental models of how systems work

(Viswanathan and Linsey 2012, Viswanathan and Linsey 2013, Viswanathan, Atilola et al. 2014). Makerspaces very likely enhance students building and prototyping skills. As they develop these skills in a community of other makers, students could learn systematic prototyping techniques, which have been shown to correlate to more effective prototypes (Camburn, Dunlap et al. 2015, Menold, Simpson et al. 2018). Furthermore, physical representations, including prototypes, help designers visualize concepts, estimate implicit attributes of designs, validate assumptions, verify functionality of ideas, and enhance communication between disparate design teams and select of the best concept (McMohan 1994, Harrison and Minneman 1997, Horton 1997, Carlile 2002, Boujut and Blanco 2003, Lidwell, Holden et al. 2003, Stowe 2008, Hannah 2009, Michaelraj 2009). Completely functional models may help designers rectify problems in their designs before production (Houde and Hill 1997). Models often function as vehicles for mutual cognition and help capture information in the design, which are not otherwise available to designers (Henderson 1999). Unfortunately, while these impacts are highly likely, little empirical data support these claims (Rosenbaum and Hartmann 2017, Weiner, Lande et al. 2018). In this paper, we choose to evaluate students' engineering design self-efficacy as an overarching measure that is highly likely affected through the many benefits makerspaces provide.

To date, one of the primary focuses of research regarding academic makerspaces has been on the implementation of these spaces at various universities and the unique aspects of these spaces (Rosenbaum and Hartmann 2017). Forest, Moore, et al. (2014) described the development of space run primarily by student volunteers and how the culture of this space developed. George-Williams (2015) described the process of identifying and establishing faculty partnerships to develop and support an on-campus makerspace. Rogers, et al. (2015) discussed the aspects of implementing a makerspace in an academic library. Spencer, et al. (2016) described aspects of developing and maintaining proper safety in a student-led makerspace and the training student volunteers complete. All of these studies provide key insights into how an academic makerspace can be established and well maintained.

Furthermore, there have been studies that have compared multiple universities' makerspaces in an effort to identify common practices. Barrett, et al. (2015) searched websites of engineering programs to compare university makerspaces. Wilczynski (2015) distributed a survey to several known academic makerspaces to compare aspects such as leadership structure, equipment, and size. Tomko, Hilton, et al. (Tomko 2017), conducted interviews with makerspace leaders in an attempt to establish guiding principles for the development and sustainment of academic makerspaces.

While these studies are useful for understanding how makerspaces can be successfully established at a university, they do not provide evidence of the benefits of these spaces for the students who use them. There have been a few data-driven studies attempting to understand these impacts. Galaleldin, et al. (2016) surveyed students active in an academic makerspace on how well the space helped them improve certain skills. This survey found that the majority of the users of the makerspace felt the space improved their problem-solving skills and design skills. While these findings are helpful for understanding the perceived impact of makerspaces of the students who use them, it does not provide a comparison to students who have not used a makerspace. Lagoudas, et al. (2016) also surveyed students who used an on-campus makerspace. Their findings included students reporting high confidence and motivation to conduct engineering design tasks. However, that study did not include students who did not use a makerspace for comparison.

There is a lack of research showing how students who use an academic makerspace compare to students who do not, and the demographic breakdown of students who use these spaces. Furthermore, there is a lack of studies on how the impact of using a makerspace varies at different universities. As such, this study seeks to help fill the gap by providing data-driven evidence of user diversity at three university makerspaces and how usage rates correlate with students' engineering design self-efficacy using data collected through survey instruments.

2.2.1 Self-Efficacy in Engineering

Theories about self-efficacy are regarded as important metrics for analyzing confidence and learning because they have proven to be good predictors for achievement and persistence. Bandura's (1997) theory of socio-cultural impacts on self-efficacy examines influences on intrinsic attitudes, motivation, and self-efficacy beliefs in four categories: 1) mastery experience (relating past experiences to the current situation), 2) vicarious experience (observation of exemplars and models), 3) social persuasion (whether or not participants have received encouraging messages or coaching/feedback from others), and 4) physiological state (emotional reactions). From this work, Bandura concludes that high levels of self-efficacy correlate with being more effective and generally more successful.

Self-efficacy toward engineering is an important metric as it has been shown to be positively related to achievement and persistence/retention in undergraduate engineering programs. Hsieh, Sullivan, Sass, & Guerra (2012) conducted a study with 297 undergraduate engineering students and found that their academic self-efficacy predicted their academic achievement in an algebra course designed for engineering students. Mamaril et al. (2016) used a self-efficacy instrument with 728 undergraduate engineering students and found that these students' intentions to persist in engineering were predicted by their general engineering and engineering skills self-efficacy levels. Concannon and Barrow (2010) conducted a study with 493 undergraduate engineering students and found a variance between female and male engineering self-efficacy, which was related to female belief in the importance of getting a good grade (i.e., A or B) and male belief in the importance of their ability to complete the required coursework. In another study conducted with 519 undergraduate engineering students, Concannon and Barrow (2009) found that though overall self-reported engineering self-efficacy predicted persistence in engineering, female and African American participants had lower self-efficacy, which was related to not feeling like they were "part of the group" (p.169). Marra, et al. (2009) conducted a multi-year study of female engineering student self-efficacy and found that over time students reported increases in general engineering self-efficacy and decreases in feelings of inclusion with significant changes found in minority female student responses. Similarly, Marra, Rodgers, Shen, and Bogue (2012) conducted a multi-year retention study by surveying 113 undergraduate students who left the engineering major and found that their decision to leave was influenced by multiple academic factors (curriculum difficulty, poor teaching, and advising) as well as a non-academic factor (lack of belonging in engineering). They also found that these factors were significantly more prominent among minority students. Alternatively, Jordan, Amato-Henderson, Sorby, and Haut Donahue

(2011) conducted a study with 394 undergraduate engineering students and found no significant differences in engineering self-efficacy among minority and majority students, which they postulated was due to the majority of those minority students actively participating in related student organization communities (e.g., National Society of Black Engineers - NSBE, Society of Hispanic Professional Engineers - SHPE, American Indian Science and Engineering Society - AISES, and Society of Women Engineers - SWE). This last study highlights the important role that a sense of community can play in student self-efficacy. As academic makerspaces have been speculated to provide a community for engineering students, this study hopes to show that students in these spaces possess higher self-efficacy for engineering design.

2.2.2 Theories of Social Integration and Involvement

Social integration and sense of feeling involved within a community are particularly important factors relating to self-efficacy. Tinto's (Tinto 1987) academic and social integration model paved the way for a sociological analysis of retention that has been popular for several decades and postulates that persistence occurs when students successfully integrate into the institution academically and socially. Integration, in turn, is influenced by pre-college characteristics and goals, interactions with peers and faculty, out-of-classroom socialization, and personal family dynamics. Similarly, Astin's (Astin 1984) theory of involvement, which is based on patterns of behavior exhibited by successful students, asserts that the keys to success and graduation are involvement and connection. Involvement refers to both formal academic or intellectual pursuits as well as co-curricular activities. Among the primary measures of academic involvement is time spent on academic studies and tasks, and the development of higher cognitive skills. Co-curricular involvement includes measures of participation in campus activities and membership in academic/honors associations and social clubs. Connection refers to bonding with peers, faculty, and staff as well as sharing the institution's values and acculturation factors. Makerspaces provide a place for community involvement in learning from peers as opposed to solely from lectures or textbooks (Taylor, Hurley et al. 2016, Tomko, Schwartz et al. 2018).

CHAPTER 3. METHODOLOGY FOR DETERMINING IMPACT OF DEVELOPING SKETCHING SKILLS IN ENGINEERING DESIGNERS

A quantitative study was conducted through by measuring the students' spatial visualization skills and sketching ability. The following section more fully describes the Introduction to Engineering Graphics Course the study is centered around, including the two version of the sketching portion of the course which form the experimental conditions. Following the description of the course, the method followed to obtain the measurements.

3.1 Engineering Graphics Course

At a public research university in the southeastern United States, all first-year students in the mechanical engineering program take an Introduction to Engineering Graphics course. This course is focused on equipping students with the ability to develop and interpret drawings and specifications for product realization. This is done through instruction in sketching and solid modeling during two 1-hour lectures and one 3-hour lab each week. For the last 20 years, this course has been taught in two primary parts (Pucha and Utschig 2012). The first five weeks of the course are dedicated to learning sketching. The lectures are dedicated to demonstrating and teaching sketching techniques as well as lectures on topics such as considerations for graphic design. The labs are dedicated to giving the students opportunities to work on the sketching methods taught in lecture with immediate feedback from TAs and the professor. The content of this portion of the course varies between two versions, which will henceforth be referred to as the Perspective

Version and Traditional Version of the course. These two versions serve as the experimental conditions of the study and are explained in more detail below.

3.1.1 Perspective Version of Sketching Curriculum

For the last five years, professors who teach the introduction to engineering graphics course have partnered with an industrial design professor to adapt the version of sketching taught to first-year industrial design students to fit in the five-week period dedicated to sketching in the mechanical engineering course (Hilton, Li et al. 2016). This version of the course focuses less on techniques considered traditional engineering drawing and more on advanced methods to generate realistic representations through free-hand sketching without the use of any supportive tools like grid paper or straight edges. The lessons covered in this version of the course include perspective, ray-tracing, shading, and complex shapes. Examples of a student's work through the semester can be seen in Figure 2.

3.1.2 Traditional Version of Sketching Curriculum.

Prior to the development of the Perspective version, a more traditional engineering drafting curricula was used in the course. Students are taught techniques that are meant to translate well into using the CAD program in the second portion of the course. These techniques include drawing three-dimensional objects, but only in isotropic views. The majority of the sketches in this version of the course are either drawn on grid paper or with heavy use of straight edge tools. While this version does give students the experience of generating sketched representations, it does not emphasize the development of the free-hand sketching skills seen in the Perspective version. An example of an in-class exercise on how to generate an isometric image from surface views can be seen in Figure 1. As sketching instruction similar to this version of the course has been shown to improve spatial visualization skills (Olkun 2003, Sorby 2009), it is of particular interest to see if the Perspective Version is equally effective at improving these skills.

3.2 Data Collection

Data was collected on both the students' spatial visualization skills and sketching ability. During the first year of the study, spatial visualization and sketching ability data was collected from the students during the first week of the course to establish a baseline, and during the last week before finals to observe any changes. After this data was analyzed, the study was continued into another semester with an additional data point. This data collection consisted only of the spatial visualization quizzes and was conducted immediately after the students completed the sketching portion of the course. This additional data point allows for better insight into what portion of the course the students were gaining spatial visualization skills.

3.2.1 Spatial Visualization Data at Beginning and End of Engineering Graphics Course

Both methods of teaching sketching are currently used in separate sections of the same freshman-level course in mechanical engineering. To study the impact of these methods, relevant skills were measured in students from both versions of the course over two semesters of the course. In total, 795 students participated in the study. The students completed pre-course and post-course evaluation using online survey distribution software to determine the impact of the course. The pre-course evaluation was given during a lab session of the first week of class. The post-course evaluation was given during the lab session two weeks before the end of the term. Students who did not complete both the pre- and post-course data collections were removed for analysis, leaving a sample size of 694. The evaluation included two scales testing spatial visualization skills.

The two spatial visualization tests were the revised Purdue Spatial Visualization Test: Rotations (PSVT:R), consisting of 30 untimed questions, originally developed by Bodner and Guay (1997) and revised by Yoon (2011), and the Mental Rotation Test (MRT), consisting of 24 questions with a time limit of 12 minutes, developed by Vandenburg and Kuse (1978) and revised by Peters (1995). Both tests present the participant with an object viewed from an initial angle and four images of similar object viewed from various angles. The participant must then select the image that shows the object from the main image rotated in space. Each test was analyzed independently, and participant submissions for each test that did not sufficiently complete the evaluation with sufficient effort (left more than half of the questions blank or gave the same answer choice for the majority of the questions) were also eliminated from the analysis. A three-question survey on effort was included following each test. No participants were eliminated based on the responses to these effort surveys alone. The eliminations resulted in a sample size of 657 (360 Perspective, 297 Traditional) for the PSVT:R, and a sample size of 675 (364 Perspective, 311 Traditional) for the MRT. The spatial visualization data for each test were analyzed between the two independent groups of students, Traditional and Perspective. As spatial visualization skills have been found to be crucial to success in engineering courses (Pleck 1991, Sorby 2009), the spatial visualization data collected pre-course was also used to determine students who were initially low-scoring in this skill. Previous work by Sorby and Veurink (2010) found that students who scored below 20 to significantly benefit from intervention. Based on these findings for the PSVT:R, students who scored below a 20 were considered low-scoring, which resulted in low-scoring PSVT:R designations for 89 students from the Perspective group (24.7%) and 75 students from the Traditional group (25.2%). For the MRT, students who scored in the bottom 33% were considered low-scoring. The cutoff for these scores was found to be scores below 11 (of a possible 24) resulting in low-scoring designations for 118 students from the Perspective group and 103 students from the Traditional group. The low-scoring students from each group were compared. Sample sizes of the spatial visualization data and adjusted low-scoring data are summarized in Table 1.

Table 1. Sample Sizes of Data Groups

	Perspective	**Traditional**	**Total**
PSVT:R	360	297	657
Low-Score PSVT:R	89	75	164
MRT	364	311	675
Low-Score MRT	118	103	221

3.2.2 Spatial Visualization Data Collection from Semester with Additional After-sketching Data Point

Data was collected via online survey from students in all nine sections of the freshman-level introduction to engineering graphics course described in the Background section. Six of these sections were taught using the Perspective method while the remaining three sections were taught using the Traditional method. The survey was conducted three times throughout the semester. The first data collection was during the first week of classes. The second was conducted the week the students turned in their final sketching assignment, about week 6. Only course material dedicated to learning free-hand sketching was covered between the first and second data collections. The third and final survey was conducted during the last full week of classes. These data collection points will be hereunto referred to as Baseline, After Sketching, and After CAD, respectively. Students completed the surveys during class time and were compensated through extra credit on a class assignment.

All three surveys consisted of two parts. The first asked students for basic identifying information. The second section consisted of two spatial visualization quizzes, the Purdue Spatial Visualization Tests for Rotations (PSVT:R) (Bodner and Guay 1997, Yoon 2011) and the Mental Rotation Test (MRT) (Vandenberg and Kuse 1978, Peters, Laeng et al. 1995). The PSVT:R consisted of 30 untimed questions, each with one correct answer. The MRT consisted of 24 questions and a time limit of 12 minutes. Each question had two correct choices and the participant was required to indicate both correct choices in order for the response to be correct. The survey given at the end of the semester consisted of a longer first section with additional demographic questions including gender, race, ethnicity, and family history.

3.2.3 Sketching Data

To evaluate the students' sketching ability and the impact the different pedagogies had on their development, the students completed pre- and post-course sketching quizzes the same lab session they completed the pre- and post-course spatial visualization quizzes. This sketching evaluation quiz was developed by Hilton, Williford et al. (2016). The final task in this quiz is to draw a camera in two-point perspective given three face views of the camera (see Figure 3). To evaluate whether or not a student improved in sketching ability, researchers scanned the pre- and post-course camera exercises of each student uploaded the scans to an online survey presented to two raters. The raters evaluated each student's pre- and post-course sketch by observing two sketches similar to Figure 3 and which sketch they considered better and if it was slightly better or much better. The order of the students and sketches were randomized to avoid a bias towards the students' group and to which sketch was the pre- or post-course sketch. These raters were instructors or graduate students with experience teaching sketching in engineering. For this study, only 4 sections of the course were analyzed: one Perspective course and one Traditional course from each semester. The analyzed data consisted of 54 students taught with the Traditional pedagogy of sketching and 67 taught with the Perspective pedagogy. To allow for inter-rater reliability, the ratings of the two raters were analyzed. The authors compared the improvement rates between students taught the Perspective pedagogy and Traditional pedagogy to determine if either pedagogy is more effective at improving sketching ability.

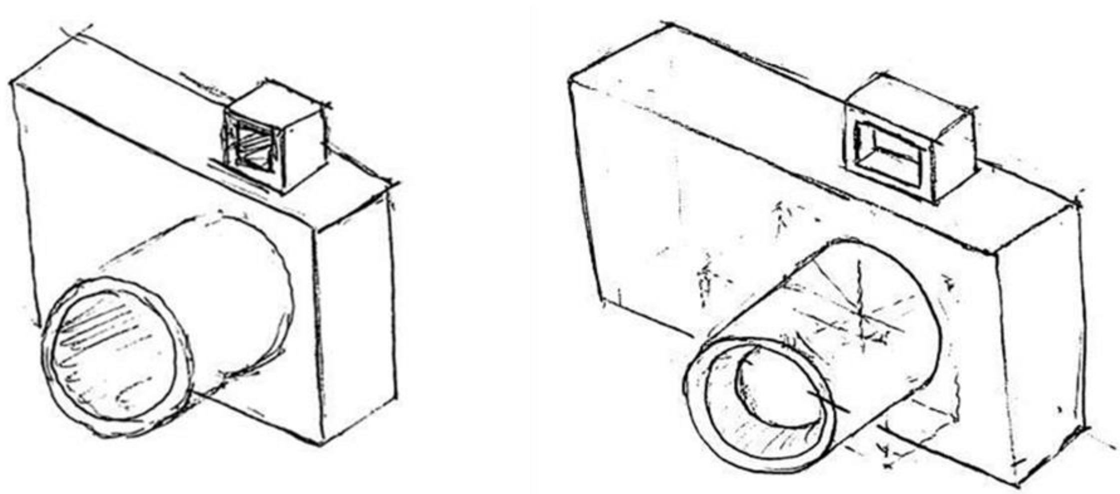


Figure 3. Example of Student Pre- and Post-Course Sketching Quiz

3.3 Analytic Process

The responses from the spatial visualization quizzes were compiled to determine which students completed all surveys during the semester. The remaining responses were discarded from the analysis. The spatial visualization quizzes were graded separately to give each student two spatial visualization scores for each survey completed. The students' responses were also screened for effort based on their spatial visualization scores.

To evaluate if spatial visualization scores changed significantly during the semester, paired t-tests were used to determine if there were any significant changes. These tests were used to evaluate all of the participants as well as separately evaluate the students in the Perspective and Traditional versions of the course. To determine if there were any significant differences between students taking each version of the course, two-sample t-tests were used. Cohen's d was used to evaluate the effect sizes and interpreted using Cohen's rule of thumb (Cohen 1988).

Due to evidence suggesting a ceiling effect, students who scored 20 or below were then sorted into initially low-scoring group based on thresholds in prior literature (Sorby and Veurink 2010, Walton, Urban-Lurain et al. 2015). The PSVT:R scores of these groups were evaluated using the same analytic process as described above. Students were not sorted into low-scoring groups based on their MRT scores due to no observed ceiling effect.

The ratings of the students sketching abilities were analyzed by counting the number of students who were found to improve or worsen and whether the difference was small or large. These counts were analyzed in two ways. The first used all four possibilities: post sketch was much worse, slightly worse, slightly better, or much better. This was analyzed using the Wilcoxon ranked-sum test. The second analysis only looked at the proportion of students whose post-course sketches were said to have improved. This was analyzed using a chi-squared test.

CHAPTER 4. METHODOLOGY FOR EVALUATING IMPACT OF INVOLVEMENT IN AN ACADEMIC MAKERSPACE

Data was gathered via survey at the three universities in the academic makerspace study. University A is a large, Hispanic-Serving university in the Southwestern United States (US) with a makerspace that had been in operation for less than a year at the time of this study. University B is a regional teaching-focused university in the Mid-Atlantic US that graduated their inaugural students from the engineering program in 2012. University C is a large, technology-focused research institute in the Southern US.

4.1 Survey Instrument

The survey was web-based, took approximately fifteen minutes to complete, and consisted of three main parts: makerspace usage, design self-efficacy, and demographics. The first portion of the survey consisted of a series of questions developed by Morocz, Levy, et al. (2016) to categorize the students' level of makerspace use. The survey was developed to measure three aspects of usage: exposure, involvement, and participation. The exposure portion of the survey is used to determine whether a participant has ever used the space. The involvement portion aims to capture the frequency of use of the space. The participation portion focused on the types of projects and activities the students carried out in the space. This includes queries about students' involvement in makerspaces prior to starting university, whether their current semester usage was different than their past usage, and the types of projects they completed in the space. The students' responses on what types of projects they completed were used to sort the students into different involvement-level groups.

The second portion of the survey instrument used in this study was the Engineering Design Self-Efficacy (EDSE) tool (Carberry, Lee et al. 2010). This validated instrument evaluates students' engineering design self-efficacy through four lenses: confidence, motivation, expectation of success, and anxiety. The students are asked to evaluate themselves through each lens on an eleven-point Likert scale (0, 10… 100). Each lens contains the same nine statements. The first statement asks about the student's self-evaluation through the lens for conducting engineering design, and the student's response is considered their engineering design (ED) score for that lens (e.g., ranking the student's confidence in their ability to conduct engineering design, or their motivation to conduct engineering design, etc.). The other eight statements in each lens probe different aspects of engineering design, such as prototyping, testing, and redesign. The student's average response to these eight items is considered their engineering design process (EDP) score for that lens (Carberry, Lee et al. 2010). This instrument includes the lens of anxiety to assist in screening responses as it is expected that it would have an inverse relationship to the other three lenses.

The third and final portion of the survey asked a variety of demographic questions. These include questions on race, ethnicity, and sex. The students were also questioned on their parents'/guardians' highest earned degrees in order to identify first-generation college students.

4.2 Survey Distribution

All three universities used the same survey for data collection, with a few small differences. Each University listed its specific makerspaces as choices for questions about involvement. University A included questions about the students' major and year in the program, but these were unnecessary for the other Universities due to their methods of data collection. University A also presented the questions for race and ethnicity questions differently, as seen in the responses in Table 5. Each University had different methods for distributing the survey to its students. For this study, the data were collected during the same calendar year at each University to provide a cross-sectional observation for each University that could also be compared between the Universities to look for common trends.

At University A, students were asked to complete the survey instrument upon initial arrival in the university-wide makerspace examined for this study. Students could choose to decline to have their data used as a part of this research study by choosing the "decline" option in the web-based survey or by leaving the survey blank; declining to participate did not impact students' access to the makerspace. Students were also requested to repeat completion of the survey each semester as long as they were still using the makerspace. Students were allowed to complete the survey prior to arrival at the makerspace.

At University B, students were asked to complete the survey during class. The survey was offered during a sophomore-level engineering design course and a junior level capstone design course. Both classes were surveyed at the end of the semester.

At University C, data were collected from students in two courses. The first was a freshman-level introduction to engineering graphics course, and the second was a sophomore-level engineering design course. Both of these courses were in the mechanical engineering curriculum. For both University B and University C, these data were collected from these courses as part of a longitudinal study. However, this study focuses on a single data collection, so these data can be compared with University A.

4.3 Analytical Procedure

Before performing analysis on the collected surveys, the data set was checked to make sure students completed the entire survey. Incomplete surveys were excluded. Further, the data were evaluated for variation between the answers for each engineering design task. For example, if the respondent marked '90' for all 36 items on the self-efficacy questionnaire, that respondent's survey was excluded. It was assumed that those respondents were simply trying to finish the survey as quickly as possible, and consequently, were not reading the questions.

After screening the data, a Pearson Correlation was conducted to compare the Engineering Design (ED) and Engineering Design Process (EDP) for each lens of the EDSE. The design of the survey was that the eight components of engineering design, which were averaged to calculate the EDP, should correlate to the response for ED (Carberry, Lee et al. 2010). All data analyzed for this study had a Pearson Correlation of 0.8 or higher. Once the student's response was validated through this check, then the student's response to the question of ED was used for the remainder of the analysis and reporting of results. Differences in EDSE were investigated based on sex, race/ethnicity, parent's education, and level of makerspace involvement. A student was considered an under-represented minority (URM) if they indicated they identified as Hispanic or Latino, African American, American Indian or Alaskan Native, Middle Eastern, or Pacific Islander. Students were considered to be a first-generation college student if they indicated the highest level of education of either of their parent/guardians was less than a bachelor's degree.

Students' involvement level was categorized into three levels based on the types of projects they had carried out using makerspace equipment. These three involvement levels are defined below:

No Involvement: students who self-reported to have never used the equipment in the makerspace.

Class-Only Involvement: students who self-reported to have used the equipment in the makerspace, but only completed course-related projects.

Voluntary Involvement: students who self-reported using the equipment in the makerspace and completed several types of projects, which can include, but was not limited to, class projects.

At University A, where the makerspace had only recently opened at the time of this data collection, very few classes required the use of makerspace equipment. Therefore, all students with involvement were considered to be in the Voluntary Involvement groups. At University B, several required courses in the engineering curriculum mandated the use of makerspace equipment. Therefore, no students at University B were considered to be in the No Involvement group. University C has students in all three groups.

Analyses of the differences in EDSE scores between various groups were conducted with t-tests to compare differences between two groups and with an ANOVA analysis with Tukey post-hoc comparisons to compare differences between the three groups. These different groupings were compared through each of the four lenses of the EDSE: confidence, motivation, expectation of success, and anxiety in conducting engineering design. Significant differences were evaluated at a threshold of 0.10 for a 90% confidence level to account for the four tests within this survey. Cohen's d was used to measure the effect sizes between groups, and Cohen's rule of thumb was used to interpret the effect sizes (Cohen 1988). Analyses of the proportion of students who use the makerspace between various groups were conducted with Chi-Squared tests for three groups or N-1 Chi-Squared tests for two groups. Effect sizes were measured using Cramer's *V* (φ_c) for three groups and Phi coefficients for association (φ) for two groups. Both Cramer's *V* and the Phi coefficients were interpreted using Cohen's rule of thumb (Cohen 1988).

CHAPTER 5. RESULTS OF STUDY ON IMPROVING SKETCHING ABILITIES IN ENGINEERING DESIGNERS

5.1 Spatial Visualization Results from Beginning and End of Semester

In total, 795 students participated in the study. Of these, 694 completed both the Baseline and After Course quizzes. Eliminations based on a lack of effort resulted in the dismissal of an additional 37 participants, leaving a total of 657 usable data points. Of these, 364 were in a Perspective version of the course and the remaining 297 were in a Traditional version.

A t-test was run between the Traditional and Perspective groups' results of both the Purdue Spatial Visualization Test on Rotations (PSVT:R) and Mental Rotation Test (MRT). To verify that the groups began at equivalent levels, a t-test was completed. The t-tests between the two groups for the Baseline PSVT:R returned a p-value of 0.73 (t=0.345, df=654), and the t-test for the Baseline MRT returned a p-value of 0.85 (t=0.193, df=673). The two groups with spatial visualization skills that were not considered to be significantly different.

After Course scores were compared to determine if the two versions had a different impact on spatial visualization skills. T-tests for After Course scores indicated no statistically significant difference between the groups for the mean (PSVT:R p=0.40, t=-0.844, df=654; MRT p=0.69, t=0.402, df=673). The pre-to-post comparison for the PSVT:R can be seen in Figure 4. All bar graphs indicate average scores for the sample and are shown with error bars indicating +/-1 standard error.

To determine if the course was improving scores, a paired t-test for the pre- and post-course was run. PSVT:R t-tests for both the Traditional group (p=0.19, t=1.32, df=295) and the Perspective group (p=0.280, t= -1.08, df=359) indicates no improvements. On further investigation, a ceiling effect was observed as 29% of the participants missed 2 or less questions. The pre to post comparison for the MRT can be seen in Figure 5. Paired t-tests were also run for both groups for the MRT and returned a p-value of <0.01 for both the Traditional (t= -13.9, df= 310) and Perspective (t= -14.9, df=363) groups, indicating students are on average improving their MRT scores in both versions of the course.

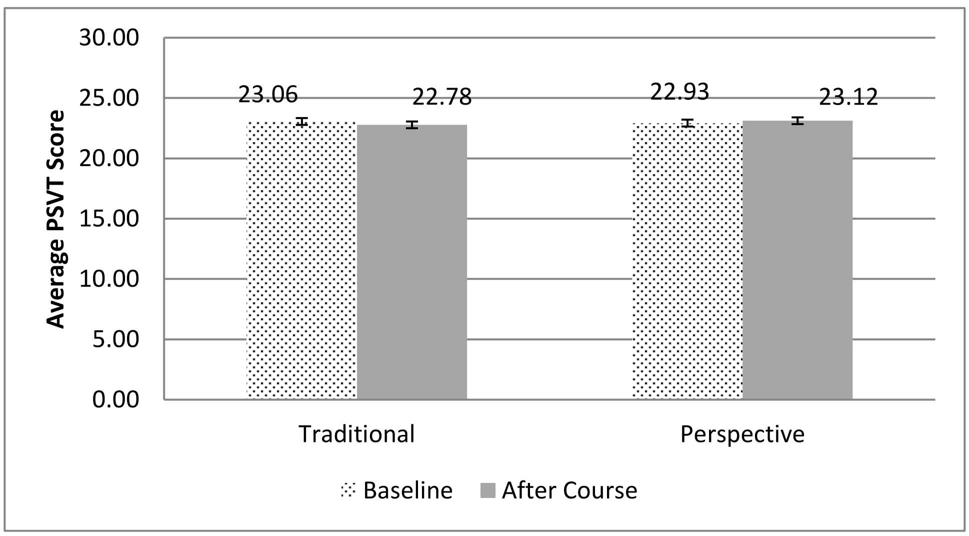


Figure 4. Baseline and After-Course Spatial Visualization scores of students in each class: Purdue Spatial Visualization Test,

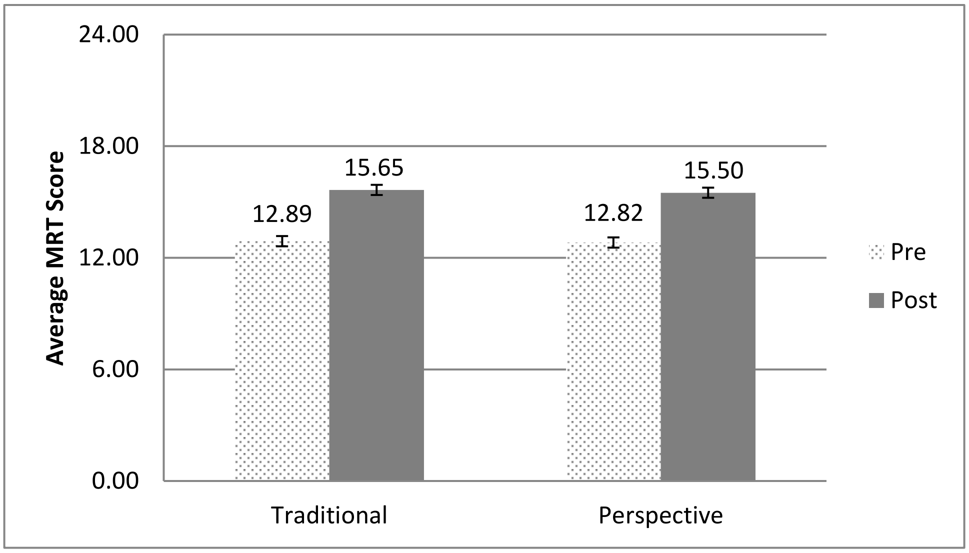
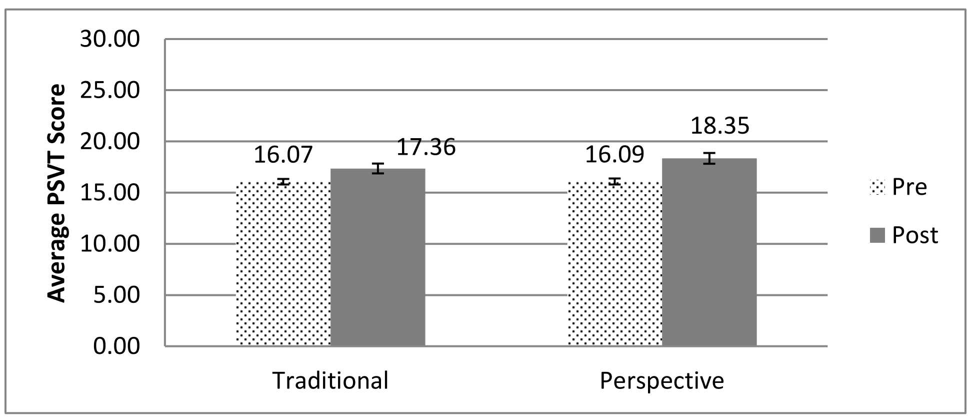


Figure 5. Baseline and After-Course Spatial Visualization scores of students in each class: Mental Rotations Test

Further investigation of the PSVT:R scores showed that a high percentage of students (29%) missed 2 questions or less on their Baseline quiz. This indicates a ceiling effect that could have kept improvements of lower-scoring students from being recognized. To further understand the impact of the course on students who began with low scores, the students determined to be low-scoring for each spatial visualization test were also compared. Comparing the PSVT:R means of the initially low-scoring students in the two groups' pre-scores returns a p-value of 0.96 (t= -0.054, df= 162), and comparing the post-course PSVT:R scores returns a p-value of 0.17 (t= 1.38, df=162). These results indicate the two groups were not statistically different at the beginning of the course or at the end of the course. Comparing the MRT means of the initially low-scoring students in the two groups' pre-scores returns a p-value of 0.68 (t= -0.408, df= 219), and comparing the post-course MRT scores returns a p-value of 0.41 (t= 1.38, df=162). These results again indicate the two groups were not statistically different at the beginning of the course or at the end of the course. Figure 6a shows the pre to post comparison of the PSVT:R averages from the initially low scoring students. Paired t-tests were run to on each group returning a p-value of 0.01 (t= -2.66, df=74) for the Traditional group and a p-value of <0.001 (t= -5.05, df=88) for the Perspective group, indicating that both approaches are improving the students' PSVT:R scores. Figure 6b shows the pre to post comparison for the MRT averages of initially low-scoring students from each group. Paired t-tests were run for each group and returned a p-value of <0.001 for both the Traditional (t= -13.9, df=310) and Perspective (t= -14.9, df=363) groups, again indicating significant improvement.

a)



b)

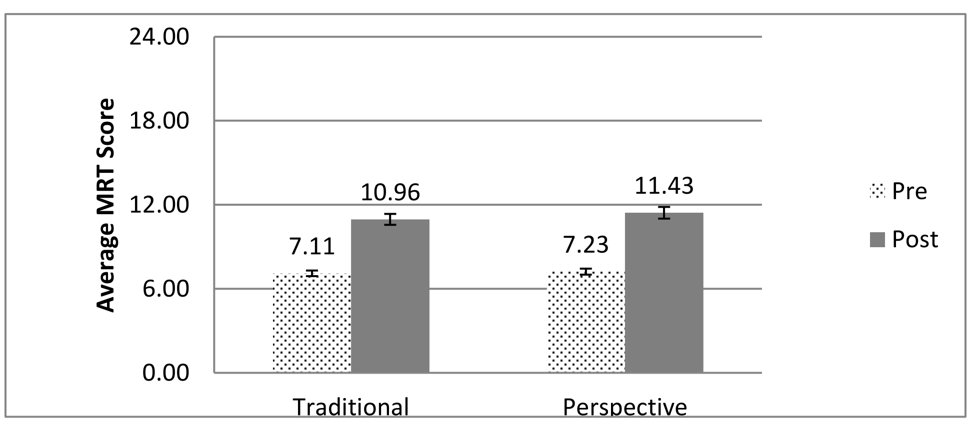


Figure 6. Pre- and Post-Course Spatial Visualization scores of Low-Scoring students in each class: A) Purdue Spatial Visualization Test, b) Mental Rotations Test

5.2 Impacts of the Sketching Portion and CAD Portion of the Course on Spatial Visualization

A total of 377 students participated in the study (99% participation). The Perspective and Traditional sections had 257 and 120 participants, respectively. After removing students who did not complete all three surveys, there were a total of 322 students, 219 in Perspective sections and 103 in Traditional sections. After following the process described in the previous section to eliminate student who showed a lack of effort, there remained a total of 202 students for the PSVT:R analysis, 139 in Perspective sections and 63 in Traditional sections, and a total of 228 students for the MRT analysis, 159 in Perspective sections and 69 in Traditional sections.

5.2.1 Results of All Students

All of the usable student data was evaluated to determine if significant changes occurred during the semester. The average PSVT:R score for each data collection point can be seen in Figure 7. A Repeated Measure ANOVA revealed there to be a significant difference between the means (F=5.40, df=2, p=0.005) with Tukey *post hoc* comparisons showing a significant difference ($p<0.05$) between the Baseline and After CAD scores with a small-to-moderate effect size (d=0.32) but not between the Baseline and After Sketching scores or the After Sketching scores and After CAD scores. This suggests that the course as a whole improved spatial visualization skills, but neither portion of the class improved spatial visualization scores individually.

Figure 7 shows the average MRT score for each data collection point. A Repeated Measure ANOVA revealed there to be a significant difference between the means

(*F*=44.83, *df*=2, *p*<0.001) with Tukey *post hoc* comparisons showing significant differences (α=0.05) between the Baseline scores and After Sketching scores with a medium-to-large effect size (d=0.77) and between the Baseline scores and the After CAD scores with a medium-to large effect size (d=0.77) but not between the After Sketching scores and the After CAD scores. This suggests that students gained spatial visualization skills during the sketching portion of the course, but did not further develop them during the CAD portion of the course. Students in the two different versions of the course were also compared to see if one version had a greater impact than the other. Figure 9 shows the average PSVT:R scores for each version of the course at each data collection point. Table 3 shows the results of t-test between the two versions' PSVT:R scores at each data collection point. These tests revealed there were no significant differences between the two courses at any data collection point.

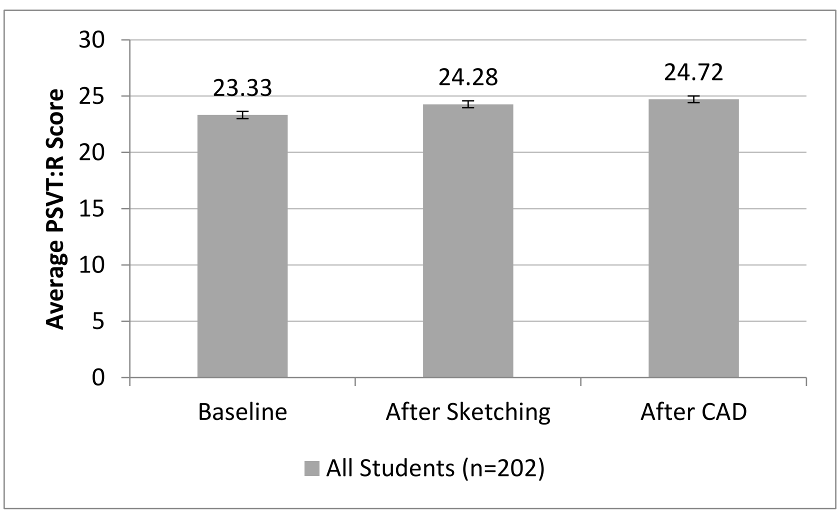


Figure 7. Average PSVT:R Scores for all participants at each data collection point shown with one standard error

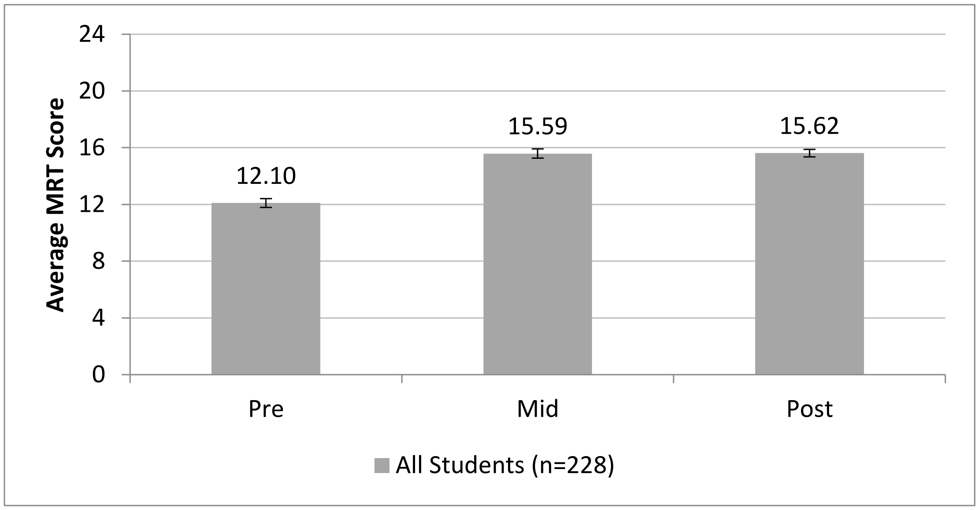


Figure 8. Average MRT scores for all participants at each data collection point shown with one standard error

Repeated Measure ANOVAs were also run for each group to see if either version had significant changes during the semester. For the Perspective version, a significant difference was found between the three groups (F=4.37, df=2, p=0.01) with Tukey *post hoc* comparisons finding a significant difference ($p<0.05$) between the Baseline score and the After CAD score with a small-to-medium effect size (d=0.36) but not between the Baseline and After Sketching scores or between the After Sketching and After CAD scores. For the Traditional Version, there were no significant differences between the three data collection points (F=1.28, df=2, p=0.28).

Figure 8 shows the MRT scores for both versions of the course at each of the data collection points. Table 2 shows the results of t-test between the two versions' MRT scores at each data collection point. These tests revealed there were no significant differences between the versions at any data point.

Repeated Measure ANOVAs were run for each group to determine significant changes during the semester. For the Perspective version, significant differences in the means were found (F=31.997, df=2, p<0.001) with Tukey *post hoc* comparisons finding a significant differences ($p<0.05$) between the Baseline and After Sketching scores with a medium-to-large effects size (d=0.76) and between Baseline and After CAD scores with a medium-to-large effect size (d=0.79) but not between the After Sketching and After CAD scores.

For the Traditional version, significant differences in the means were found (F=12.73, df=2, p<0.001) with Tukey *post hoc* comparisons finding a significant differences ($p<0.05$) between Baseline and After Sketching scores with a medium-to-large effects size (d=0.77) and between Baseline and After CAD scores with a medium-to-large effect size (d=0.72) but not between the After Sketching and After CAD scores.

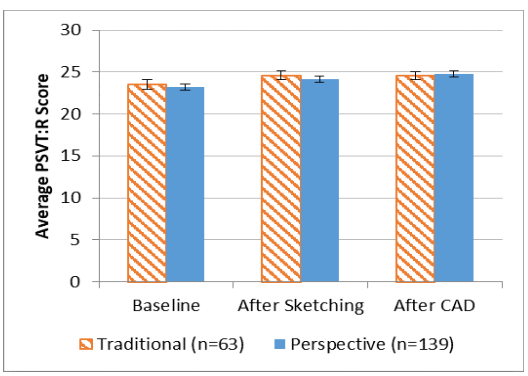


Figure 9. Average PSVT:R scores for participants in each version of the course at each data collection point shown with one standard error

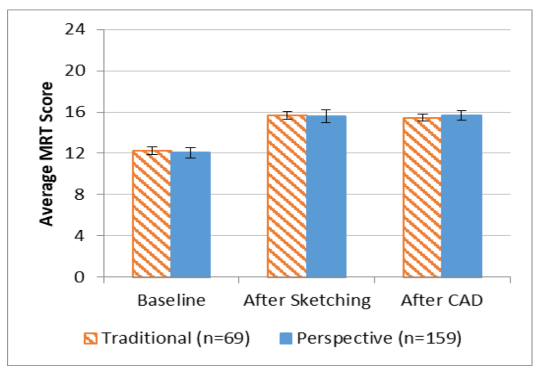


Figure 10. Average MRT scores for participants in each version of the course at each data collection point shown with one standard error

Table 2. Results of t-tests of MRT scores between Perspective and Traditional versions

	t	*df*	*p*
Baseline	-0.28	226	0.782
After Sketching	-0.12	226	0.904
After CAD	0.42	226	0.676

Table 3. Results of t-tests of PSVT:R scores between Perspective and Traditional versions

	t	*df*	*p*
Baseline	-0.41	200	0.680
After Sketching	-0.71	200	0.479
After CAD	0.34	200	0.731

5.2.2 Results of Initially Low-Scoring Students

Of the 202 students analyzed, 62 of the students missed three or fewer questions on the PSVT:R. This suggested to the authors that a ceiling effect is partially causing the lack of significant difference between Baseline scores and After Sketching scores such as those seen in MRT scores. For this reason, low-scoring students were further investigated. Walton, et al. (2015) distinguish students who score between 0 and 17 as “failing”, students who scored between 18 and 20 as “marginally passing”, and students who scored 21 and above as “passing”. Using these guidelines, we further investigated 43 students (29 Perspective, 14 Traditional) who initially scored between 0 and 20, and 26 students (18 Perspective and 8 Traditional) who scored between 0 and 17.

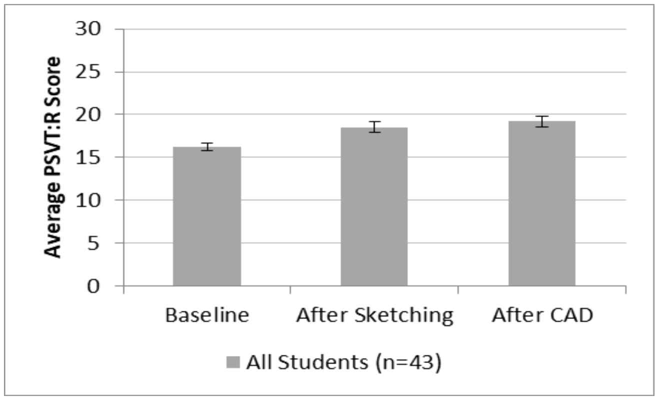


Figure 11. Average PSVT:R scores for all participants who had a Baseline score between 0 and 20 at each data collection point shown with one standard error

5.2.2.1 Students Initially Scoring 0 to 20.

Figure 11 shows the PSVT:R scores at each data collection point for students who initially scored between 0 and 20. A Repeated Measures ANOVA revealed a significant difference between the three data points (F=7.29, df=2, p=0.001) with Tukey *post hoc* comparisons showing differences between the Baseline and After Sketching scores with a medium-to-large effect size (d=0.60) and between Baseline and After CAD scores with a medium-to-large effect size (d=0.79) but not between After Sketching and After CAD scores. These results echo those of the MRT results from the entire participant population.

The PSVT:R scores for students who initially scored between 0 and 20 can be seen in Figure 12. To determine if either version of the class had a greater impact on students with low initial spatial visualization skills, t-tests were run at each data collection point. The results of these t-tests can be seen in Table 4 and indicate no significant differences between the groups at any data collection point. Repeated Measure ANOVAs were run on each group to determine if significant changes during the semester occurred. For the

Perspective method, significant differences were found (*F*=3.64, *df*=2, *p*=0.031) with Tukey *post hoc* comparisons revealing a significant difference between the Baseline and After CAD averages with a medium-to-large effect (*d*=0.70) but not between the Baseline and After Sketching scores or between the After Sketching and After CAD Scores. For the Perspective group, the ANOVA found a significant difference between the data collection points (*F*=4.54, *df*=2, *p*=0.017) with Tukey *post hoc* comparisons showing significant differences between the Baseline and After Sketching scores with a large effect size (*d*=0.99) and between the Baseline and After CAD scores with a large effect size (*d*=0.99) but not between the After Sketching and After CAD scores.

5.2.2.2 <u>Students Initially Scoring 0 to 17.</u>

The final group of interest investigated were those students who initially scored below 18 on the Baseline PSVT:R. The average scores for these students can be seen in Figure 13. A Repeated Measures ANOVA revealed a significant difference between the data collection points (*F*=6.53, *df*=2, *p*=0.002) with Tukey *post hoc* tests showing differences between the Baseline and After Sketching scores with a medium-to-large effect (*d*=0.96) and between the Baseline and After CAD scores with a large effect (*d*=0.96).

Due to a small samples size from the Traditional version of the course, comparisons were not made between the two versions of the course for students who initially scored between 0 and 17 on the Baseline PSVT:R.

Table 4. Results of t-tests of PSVT:R scores between Perspective and Tradtional versions for students with intial PSVT:R scores 0-20

	t	*df*	*p*
Baseline	0.25	41	0.807
After Sketching	-0.97	41	0.340
After CAD	-0.21	41	0.833

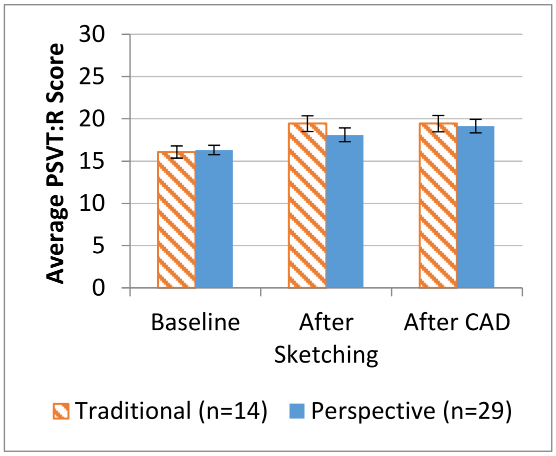


Figure 12. Average PSVT:R scores for participants in each version of the course with Baseline score between 0 and 20 at each data collection point shown with one standard error

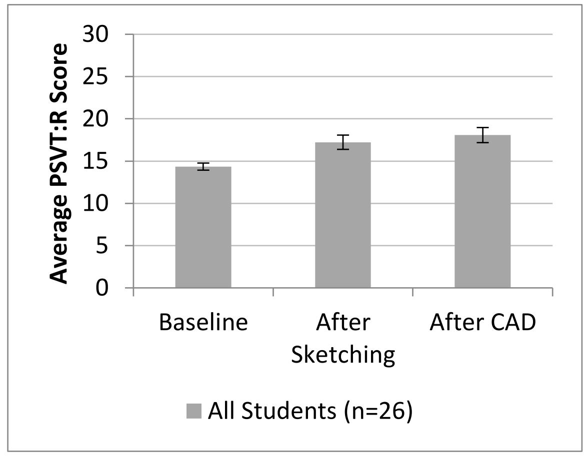


Figure 13. Average PSVT:R scores for all participants who had a Baseline score between 0 and 17 at each data collection point shown with one standard error

The results as a whole suggest that both versions of the engineering course improve students' spatial visualization skills. Furthermore, the results suggest that this improvement comes mostly from the portion of the class dedicated to learning free-hand sketching techniques and not during the portion of class dedicated to CAD modeling. This is true for all students, but especially for students with initially poor spatial visualization skills. The average score for students who begin with a PSVT:R score between 0 and 20 actually rises above the "failing" mark of 17 after the sketching portion of the course. This is significant as Sorby and Veurink (2010) has found that students with scores higher than 17 are more likely to finish their engineering degrees.

Finally, the results indicated no significant differences between students in each version of the class. This finding is expected as the Traditional version of the class has begun implementing more of the teaching methods found in the Perspective version of the course.

5.3 Results on Improving Sketching Ability

Through the steps laid out in the Methodology section, preliminary data was obtained. Each data point was given one of four designations:

1. Pre-course sketch was much worse
2. Pre-course sketch was slightly worse
3. Post-course sketch was slightly better
4. Post-course sketch was much better

The ratings of both evaluators were compared to one another using a Pearson correlation to determine if the ratings can be considered reliable. When comparing the initial ratings using the quantitative scale outlined at the beginning of this section, the two raters have a Pearson correlation of 0.68, indicating a strong agreement. When considering the data as binary (improved or worsened), the raters have a Cohen's Kappa of 0.62, indicating a substantial agreement.

5.3.1 Ranked Sum Analysis

The counts of each designation for how the student improved or worsened in sketching can be seen in Figure 14 along with a graphical representation of the proportions of each designation. Using a Wilcoxon ranked sum test, students taught using the perspective pedagogy improved their sketching ability significantly more than students in taught with the Traditional pedagogy with a small effect size ($W = 2213$, $p = 0.021$). Only one rater's designations were used to analyze the data.

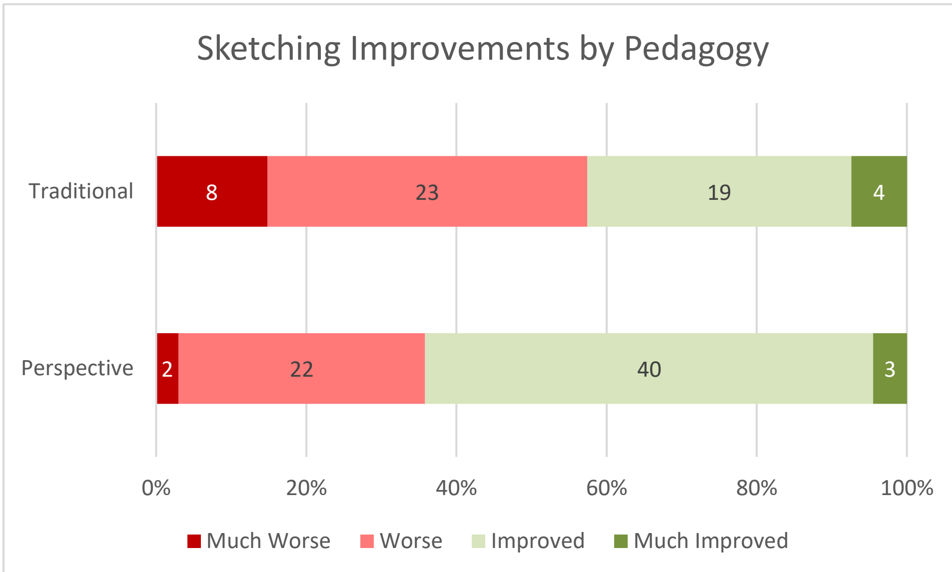


Figure 14. Counts and proportions of Sketching Improvements by Pedagogy

5.3.2 Chi-squared Analysis

The proportion of students who were found to have improved were analysed using a chi-squared test on proportions. Students taught using the Perspective Pedagogy were significantly more likely to improve their sketching ability than student taught using the Traditional pedagogy. Both the Wilcoxon ranked-sum test and the chi-squared text on proportions indicate the Perspective method for being a more reliable way to improve sketching ability while the previous analyses show the Perspective pedagogy maintains the improvements to spatial visualization associated with more traditional methods of teaching sketching in engineering curricula.

5.3.3 Changes in Spatial Visualization based on Improvements in Sketching Ability

A final analysis was done to explore a correlation between improved sketching ability and improved spatial visualization abilities. This was carried out by dividing the students into two groups based on whether or not their post-course sketch was found to have been an improvement over their pre-course sketch, regardless of what sketching pedagogy they were taught. This resulted in 50 students whose sketching ability worsened and 60 whose sketching ability improved. Figure 15 shows how each group's PSVT:R score changed during the course. Paired t-tests were used to determine that the students whose sketching worsened were not found to have a significant improvement ($t=0.659$, $df=49$, $p=0.513$) while the students whose sketching improved were found to significantly improve their PSVT:R score ($t=3.04$, $df=59$, $p= 0.0035$). This indicates a measurable correlation between improving sketching ability and improving spatial visualization skills.

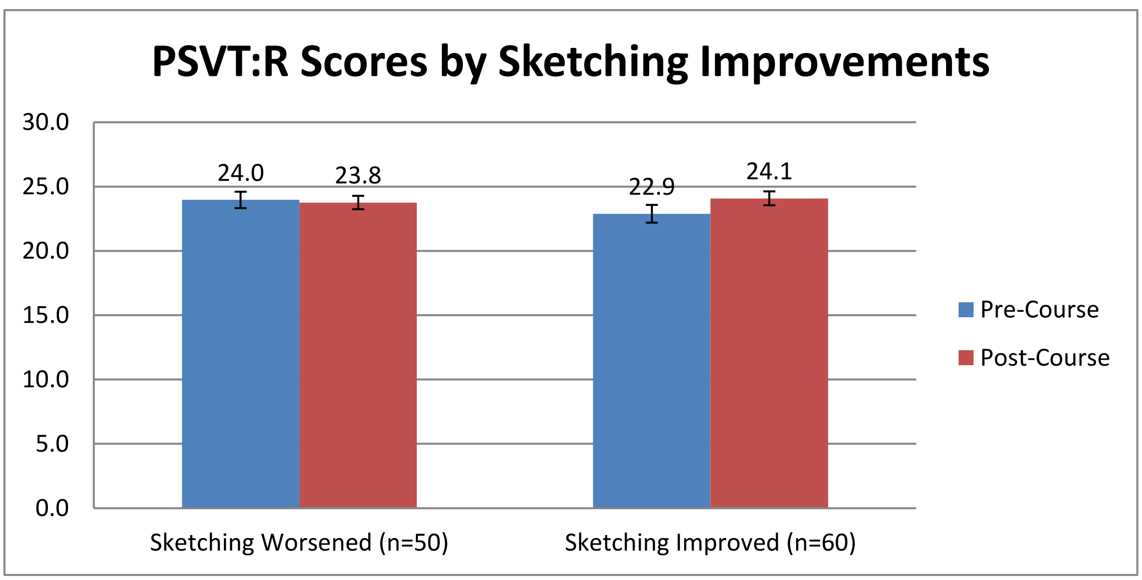


Figure 15. Average Pre- and Post-Course Purdue Spatial Visualization Test based on Improvements in Sketching Ability.

CHAPTER 6. RESULTS FROM MAKERSPACE STUDY COMPARING STUDENTS AT THREE UNIVERSTIES

6.1 Results at Each University

At University A, the survey was given to 208 students. As the survey was voluntary, several students did not complete the whole survey. This resulted in the removal of 38 incomplete surveys and additional 3 surveys removed for failing the screening check described previously, resulting in 167 total surveys analyzed. Of these, 58 students were not in an Engineering or Engineering Technology Major. Since the other two universities only considered students in engineering programs, these 58 students were excluded from further analysis, resulting in 109 analyzed surveys. Data were collected in class at University B and University C, so there were not incomplete surveys. However, surveys that failed the screening test were still removed. At University B, the survey was taken by 145 students. After applying the exclusion criteria, 140 surveys were analyzed. At University C, the survey was taken by 728 students. After applying the exclusion criteria, 657 were analyzed. The demographics of the students whose surveys were analyzed at each university are shown in Table 5. Students who left a demographic question blank (or marked 'prefer not to respond') were not analyzed in any group for that demographic but were still analyzed as a part demographic sub-groups for questions they did answer. Percentages are based on the total number of analyzed students at each university.

Table 5: Demographics of Participants at each University

	University A		University B		University C	
Survey Question	n	%	n	%	n	%
What sex do you identify as?						
Female	15	13.8%	32	22.9%	158	24.0%
Male	95	86.2%	105	75.0%	490	74.6%
Prefer Not to Disclose	0	0%	2	1.4%	4	0.6%
Other	0	0%	1	0.7%	5	0.8%
What Race/ethnicity do you identify with? (Select all that apply)[1]						
African American/Black	6	5.5%	10	7.1%	32	4.9%
American Indian or Native Alaskan	1	0.9%	0	0%	0	0%
Asian	3	2.8%	9	6.4%	164	25.0%
Hawaiian or other Pacific Islander	0	0%	0	0%	0	0%
Hispanic, or Latino	35	32.1%	11	7.9%	56	8.5%
Middle Eastern	3	2.8%	1	0.9%	8	1.2%
White/Caucasian	62	56.9%	114	81.4%	453	68.9%
Other	1	0.9%	3	2.1%	13	2.0%
I prefer not to answer	7	6.4%	3	2.1%	12	1.8%
What is your current classification at [University]?[2]						
Freshman	11	10.1%	0	0%	426	64.8%
Sophomore	10	9.2%	85	60.7%	231	35.2%
Junior	36	33.0%	55	39.8%	0	0%
Senior	51	46.8%	0	0%	0	0%
Graduate Student	1	0.9%	0	0%	0	0%

[1]The race/ethnicity question at University B and University C did not include 'Hispanic or Latino' as an option, but rather as a separate question, 'Do you identify as Hispanic or Latino?'
[2]The question of classification was not asked on the survey for University B and University C. Instead, this number was determined by the course the survey was administered in.

6.1.1 University A

Average EDSE scores were analyzed for three demographic designations: sex, minority status, and family education history. The values of t-tests and Cohen's effect size can be seen in Table 6. Female students are found to have a statistically significant lower confidence when conducting engineering design tasks than their male counterparts with a medium effect size. No significant differences were seen between female and male students for motivation, expectation of success, and anxiety while conducting engineering design task. Students classified as URMs were found to have statistically significant higher levels of anxiety while conducting engineering design with a small-to-medium effect size. There were no statistically significant differences for confidence, motivation, or expectation of success. Further, there are no significant differences between students whose parents did not receive college degrees (1st Gen) and those who are not.

Table 6: Averages and results of t-tests between Sub-Groups' EDSE for University A

Confidence						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	15	58.00	-1.82	108	0.071†	0.51
Male	94	69.37				
URM	45	70.00	0.73	101	0.47	0.14
non-URM	58	66.72				
1st Gen	43	67.91	0.03	107	0.98	0.01
non-1st Gen	66	68.03				
Motivation						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	15	85.33	0.04	108	0.97	0.01
Male	94	85.16				
URM	45	85.33	0.00	101	1.00	0.00
non-URM	58	85.34				
1st Gen	43	85.81	-0.28	107	0.78	0.05
non-1st Gen	66	84.85				
Expectation of Success						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	15	70.00	-0.55	108	0.58	0.15
Male	94	73.05				
URM	45	73.56	0.16	101	0.87	0.03
non-URM	58	72.93				
1st Gen	43	74.65	-0.92	107	0.36	0.18
non-1st Gen	66	71.06				
Anxiety						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	15	36.67	-0.93	108	0.35	0.26
Male	94	45.26				
URM	45	50.67	1.86	101	0.066†	0.37
non-URM	58	38.62				
1st Gen	43	49.77	1.57	107	0.12	0.31
non-1st Gen	66	39.70				

†Significant at $\alpha=0.10$

6.1.1.1 Proportion of Demographic Subgroups who are Voluntarily Involved at University A.

The number of students from each demographic sub-group at University A can be seen in Table 7. Chi-squared tests reveal that men are significantly more likely to be voluntarily involved with a small-to-moderate effect size (χ^2=3.03, df=1, p=0.08, φ=0.16). However, there is no significant difference based on minority status (χ^2=1.04, df=1, p=0.31) or based on the students' parents' highest degrees (χ^2=0.52, df=1, p=0.47).

Table 7. Involvement Level by Demographic Sub-Group

Involvement Level	Total	Male	Female	URM	Non-URM	1st Gen	Non-1st Gen
Voluntary	27	26	1	8	15	7	13
No Involvement	82	68	14	37	42	36	46
Total	109	94	15	45	57	43	59

6.1.1.2 Correlation of Makerspace Participation with Engineering Design Self-Efficacy for University A.

Of the 109 participants at University A, 27 participants (24.8%) had used an academic makerspace and were labeled as Voluntary Involvement. A comparison of Voluntary Involvement and No Involvement students is shown in Figure 16, and the results of t-tests along with effect size can be seen in Table 8. Students who voluntarily used an academic makerspace were found to have higher levels of confidence, motivation, and expectation of success when conducting engineering design than students who had not used a makerspace. This difference was statistically significant, with a small-to-medium effect. There was no significant difference for levels of anxiety while conducting engineering design between makerspace users and non-users.

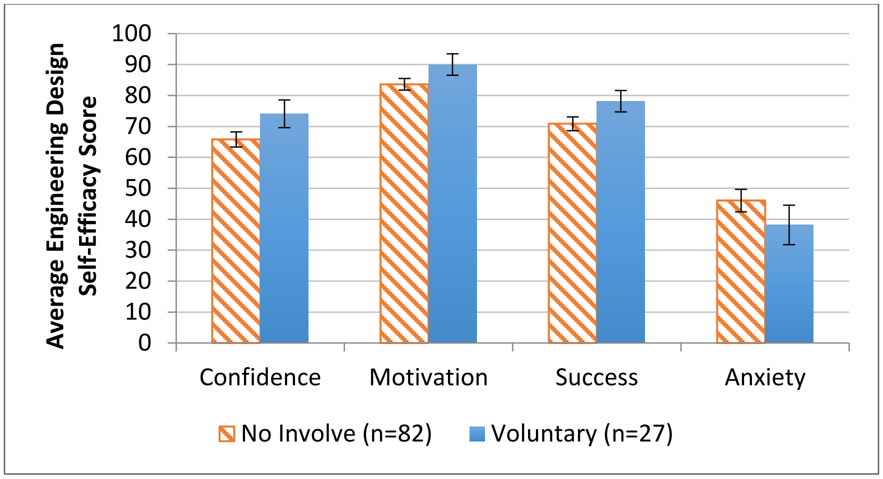


Figure 16: Average Engineering Design Self-Efficacy Scores across Involvement Types at University A. Shown with ±1 Standard Error

Table 8. Statistics for EDSE comparisons based on makerspace Involvement for University A

EDSE	***t***	***df***	***p***	***d***
Confidence	1.66	108	0.099†	0.37
Motivation	1.66	108	0.10†	0.37
Success	1.67	108	0.098†	0.37
Anxiety	-1.07	108	0.285	0.24
Key:	†Significant at α=0.10			

6.1.2 University B

The average Engineering Design Self-Efficacy (EDSE) scores were compared between different groups of students at University B, as seen in Table 9. As with University A, female students were found to have significantly lower confidence than their male counterparts. However, under-represented minorities were found to have lower anxiety than their counterparts.

Table 9. Averages and results of t-tests between Sub-Groups' EDSE for University B

Confidence						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	32	80.94	2.01	135	0.046*	0.406
Male	105	86.00				
URM	21	86.19	0.59	133	0.553	0.141
non-URM	114	84.39				
1st Gen	17	83.53	0.31	137	0.756	0.08
non-1st Gen	122	84.59				
Motivation						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	32	85.63	0.24	135	0.81	0.05
Male	105	84.86				
URM	21	88.10	0.99	133	0.326	0.234
non-URM	114	84.39				
1st Gen	17	83.53	0.32	137	0.753	0.08
non-1st Gen	122	84.84				
Expectation of Success						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	32	81.56	0.62	135	0.539	0.125
Male	105	83.05				
URM	21	86.19	1.47	133	0.145	0.348
non-URM	114	82.02				
1st Gen	17	82.94	0.23	137	0.818	0.06
non-1st Gen	122	82.21				
Anxiety						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	32	41.88	0.62	135	0.536	0.125
Male	105	38.10				
URM	21	28.57	1.80	133	0.074†	0.427
non-URM	114	41.32				
1st Gen	17	38.82	0.01	137	0.995	0.00
non-1st Gen	122	38.77				

Key: *Significant at α=0.05, †Significant at α=0.10

6.1.2.1 *Proportion of Demographic Subgroups who are Voluntarily Involved at University B*

An analysis of the proportions of each demographic sub-group and their use was conducted. The proportion of each sub-group who are voluntarily involved can be seen in Table 10. None of the sub-groups are significantly more involved than their counterparts. This includes sex (χ^2=0.24, df=1, p=0.621), minority status (χ^2=0.31, df=1, p=0.577), and parents' education (χ^2=0.24, df=1, p=0.626).

Table 10. Involvement Level by Demographic Sub-Group at University B

Involvement Level	Total	Male	Female	URM	Non-URM	1st Gen	Non-1st Gen
Voluntary	41	31	8	7	32	6	35
Class-Only	99	74	24	14	82	11	87
Total	140	105	32	21	114	17	122

6.1.2.2 Correlation of Makerspace Participation with Engineering Design Self-Efficacy.

Of the 140 students analyzed at University B, 41participants (29.3%) were voluntarily involved in the makerspace. Figure 17 shows the averages of each EDSE score for the levels of involvement. The t-tests comparing the two groups are seen in Table 11. There are no statistically significant differences between the Voluntarily Involved and Class-Only Involved students for University B.

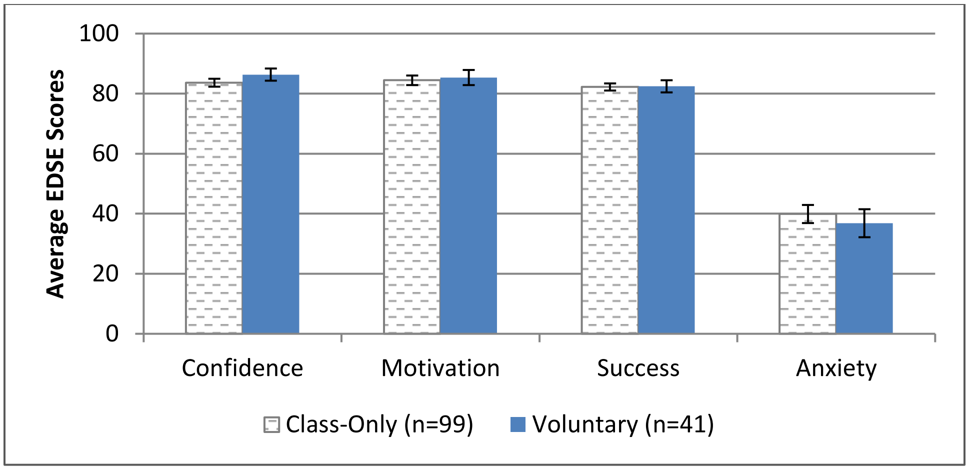


Figure 17. Average Engineering Design Self-Efficacy Scores across Involvement Types at University B. Shown with ±1 Standard Error

Table 11. Statistics for EDSE comparisons based on makerspace Involvement for University B

EDSE	***t***	***df***	***p***	***d***
Confidence	1.11	138	0.268	0.207
Motivation	0.31	138	0.756	0.058
Success	0.10	138	0.924	0.018
Anxiety	-0.55	138	0.582	0.103

6.1.3 University C

The average Engineering Design Self-Efficacy (EDSE) scores were compared between different groups of students at University C, as seen in Table 12. Female students were found to have significantly lower expectations of success and higher anxiety than their male counterparts. However, under-represented minorities were found to have lower anxiety than their counterparts. Additionally, 1st-Generation students had higher anxiety than their counterparts.

6.1.3.1 Proportion of Demographic Subgroups who are Voluntarily Involved at University C

The proportions of each demographic sub-group at University C can be seen in Table 13. As with University A, female students were found to be significantly less likely to be voluntarily involved than their male counterparts with a moderate-to-large effect (χ^2=36.93, df=1, p<0.001, φ=0.52). Neither minority status (χ^2=1.17, df=1, p=0.279) nor parents' education (χ^2=0.14, df=1, p=0.705) were correlated with a significant difference in the proportion of students who were voluntarily involved.

6.1.3.2 Correlation of Makerspace Involvement with Engineering Design Self-Efficacy at University C

The final analyses conducted for each university sought to determine the impact of being involved in an academic makerspace on Engineering Design Self-Efficacy. The average scores are shown in Figure 18 with the results of ANOVA and Tukey *post hoc* tests listed in Table 14. The Voluntarily Involved students have significantly higher Confidence, Motivation, and Expectation of Success when conducting engineering design tasks when compared to students with No Involvement and with students with Class Only involvement. Voluntarily Involved students also have lower Anxiety when conducting engineering design.

Table 12. Averages and results of t-tests between Sub-Groups' EDSE for University C

Confidence							
Demographic	**n**	**Average**	**SD**	**t**	**df**	**p**	**d**
Female	158	73.29	18.28	0.67	646	0.505	0.06
Male	490	74.33	16.53				
URM	101	76.24	16.42	-1.38	646	0.167	0.15
non-URM	547	73.69	17.08				
1st Gen	114	71.93	18.33	1.5	652	0.133	0.16
non-1st Gen	540	74.56	16.64				
Motivation							
Demographic	**n**	**Average**	**SD**	**t**	**df**	**p**	**d**
Female	158	77.28	20.80	1.38	646	0.168	0.07
Male	490	79.73	19.02				
URM	101	82.57	18.04	-1.93	646	0.054†	0.21
non-URM	547	78.50	19.69				
1st Gen	114	78.51	19.47	0.37	652	0.712	0.24
non-1st Gen	540	79.26	19.44				
Expectation of Success							
Demographic	**n**	**Average**	**SD**	**t**	**df**	**p**	**d**
Female	158	70.76	18.90	1.71	646	0.088†	0.16
Male	490	73.55	17.53				
URM	101	75.15	17.53	-1.37	646	0.17	0.15
non-URM	547	72.49	17.94				
1st Gen	114	72.02	18.73	0.56	652	0.574	0.06
non-1st Gen	540	73.06	17.70				
Anxiety							
Demographic	**n**	**Average**	**SD**	**t**	**df**	**p**	**d**
Female	158	41.39	26.72	-2.77	646	0.006*	0.25
Male	490	34.45	27.60				
URM	101	38.61	30.27	-0.96	646	0.338	0.1
non-URM	547	35.76	26.94				
1st Gen	114	41.49	28.94	-2.31	652	0.021*	0.24
non-1st Gen	540	34.98	27.04				
Key: *Significant at α=0.05, †Significant at α=0.10							

Table 13. Involvement Level by Demographic Sub-Group at University C

Involvement Level	**Total**	**Male**	**Female**	**URM**	**Non-URM**	**1st Gen**	**Non-1st Gen**
Voluntary	276	218	52	40	230	47	230
Class-Only	104	77	26	14	89	16	89
No Involvement	277	195	80	47	228	51	226
Total	657	490	158	101	547	114	545

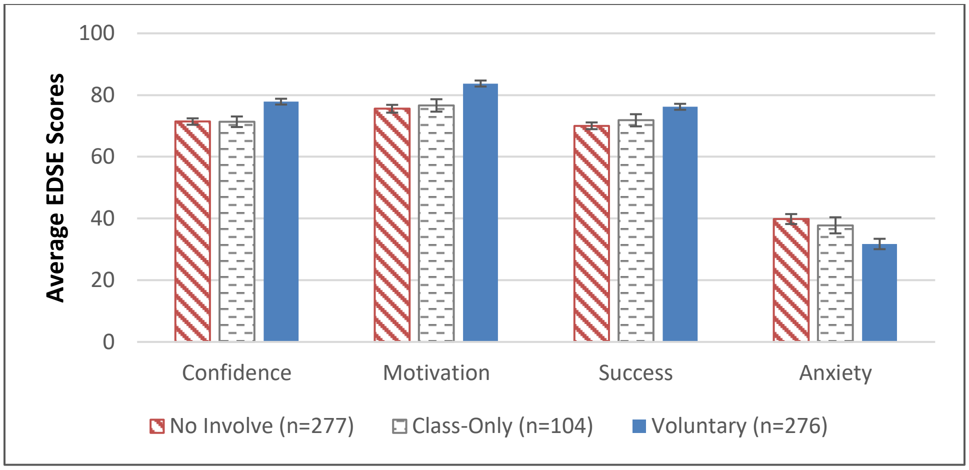


Figure 18. Average Engineering Design Self-Efficacy Scores across Involvement Types at University C Shown with ±1 Std. Error

Table 14. ANOVA and Tukey tests for EDSE comparisons based on makerspace involvement for University C

EDSE	ANOVA			Tukey (Vol-CO)		Tukey (Vol-None)		Tukey (CO-None)	
	F	dfs	p	diff	d	diff	d	diff	d
Confidence	12.07	2, 654	<0.001	6.51*	0.39	6.45*	0.39	-0.06	0.004
Motivation	13.84	2, 654	<0.001	7.10*	0.37	8.17*	0.43	1.07	0.06
Success	8.66	2, 654	<0.001	4.37†	0.25	5.96*	0.34	1.79	0.10
Anxiety	6.33	2, 654	0.002	-6.05	0.22	-8.08*	0.30	-2.03	0.07

Key: *Significant at α=0.05 †significant at α=0.10

6.2 Comparison across the Three Universities

The data demonstrated some common findings across the three universities as well as some differences. The possible reasons for the differences will be hypothesized, but future work must test these hypotheses. Note that only University C had students in all three levels of involvement: No Involvement, Class Only Involvement, and Voluntary Involvement. Across all four categories of the EDSE, no differences appeared between students who used the makerspaces for Class Only and No Involvement groups at

University C, but choosing to use the makerspace was correlated with superior EDSE across all four lenses (Figure 18). Consistent with this, University A also demonstrates higher Confidence, Motivation, and Expectation of Success for students involved in the makerspace as compared to those not involved (Figure 16). At University B, however, there were no statistically significant differences between Class-Only and Voluntary Involvement groups. Owing to a curriculum that sends all engineering students to a makerspace as freshmen, there were zero No Involvement students surveyed at University B. It is very possible that the design curriculum at University B effectively provides a high degree of involvement in the makerspaces for all students, which therefore provided improvements to their engineering design self-efficacy from class-only involvement at that institution. There may be a threshold at which additional makerspace involvement and design projects do not further increase design self-efficacy (EDSE). Future work should seek to determine this threshold such that all students could be provided with the required level of design opportunities to increase their design self-efficacy.

The differences between No Involvement and Voluntary Involvement groups observed at Universities A and C could be because the makerspaces helped students gain Confidence, Motivation, and Expectation of Success. Alternatively, students who already had greater Confidence, Motivation, or Expectation of Success may naturally become voluntarily involved in makerspaces. Data from University C suggest that freshman who were initially more motivated to conduct design tended to become involved in the makerspaces more than did students with initially lower motivation (Hilton, Tomko et al. 2018). These same data also indicated students who chose to become involved in the makerspace during their freshman year showed greater Confidence and Expectation of

Success at the end of the semester than did students who did not become involved, even though both groups started at similar levels.

Table 15: Summary of Statistically Significant Differences Observed Across the Three Universities

Measure - Group	University A	University B	University C
EDSE - Sex	Females: Lower Confidence	Females: Lower Confidence	Females: Lower Expectation of Success Higher Anxiety
EDSE - URMs	URMs: Higher Anxiety	URMs: Lower Anxiety	URMs: Higher Motivation
EDSE - 1st generation	------	------	1st Gen: Higher Anxiety
Involvement - Sex	Females: Lower Involvement	------	Females: Lower Involvement
Involvement - URM	------	------	------
Involvement – 1st generation	------	------	------
EDSE - Involvement	Users: Higher Confidence Higher Motivation Higher Expectation of Success	------	Voluntary Users: Higher Confidence Higher Motivation Higher Expectation of Success Lower Anxiety*

Key: ------ No Statistically Significant Differences

*Voluntary Users at University C are only significantly less anxious than students with No Involvement (see Figure 18)

A couple of key demographic groups who are historically underrepresented in engineering fields were found to have lower engineering design self-efficacy at all three universities. Female students were found to have lower confidence when conducting engineering design than their male counterparts at University A and University B and have lower expectation of success, and higher anxiety at University C. First-generation college students were found to have higher levels of anxiety than non-first generation students at University C.

The groups who have shown lower engineering design self-efficacy scores in this study, however, are also the groups who have shown a lower participation rate in the makerspace. At University C, male students were four times more likely to be a user of a makerspace than women. Based on these findings, as well as a previous study reported in the background demonstrating no significant differences in engineering self-efficacy among minority and majority students likely due to active participation in related student organization communities (Jordan, Amato-Henderson et al. 2011), more effort should be made to increase the participation of these under-represented groups in academic makerspaces. Previous work describes makerspaces as communities of practice (Halverson and Sheridan 2014), and it is important that students see these makerspaces as *welcoming* communities of practice in order to release the gains in engineering design self-efficacy that, as research is beginning to demonstrate, makerspaces can afford to students.

Another interesting finding is the fact that female students at both University A and University C were significantly less likely to be voluntarily involved than their male counterparts, but the same was not found at University B. One hypothesis for this is the amount of required work in the makerspace for class projects maybe removing the barriers present for female students to feel a belonging in the space. Another contributing factor may be the higher percentage of female faculty at University B. Further studies into how the makerspace at University B seems to be more inclusive for women could lead to significant findings on how this inclusion can be spread to other academic makerspaces or even other extra-curricular engineering groups.

Finally, while the data presented in this paper showed a correlation between the use of an academic makerspace and engineering design self-efficacy, it did not prove causation. It is possible that students with higher EDSE were more likely to become involved in a makerspace. In order to truly understand the correlations between EDSE and involvement in academic makerspaces, a longitudinal study was conducted. The results of this study are presented in the following chapter.

CHAPTER 7. RESULTS OF LONGITUDINAL MAKERSPACE STUDY AT TWO UNIVERSITIES

This chapter presents the results from the longitudinal studies conducted over five years at two Universities. These two universities were presented in the previous chapters as University B and University C. The two universities' results are presented separately to avoid impacts due to extraneous variables such as differences in timing of data collection. First, the differences in engineering design self-efficacy (EDSE) and GPA between participants based on their demographics are analyzed to gain a better understanding the participants in the study and how this changes as the participants progress though the engineering curricula. Second, the proportion of students who become Voluntary Users based on their demographics is presented. Third, analysis of the EDSE and GPA of students based on their use of the academic makerspace is presented. Fourth, an analysis of how a class project may influence involvement in academic makerspace is presented. Finally, an analysis of how involvement impacts retention in mechanical engineering is presented.

7.1 Demographics of Participants and Correlation to Measured Variables

The breakdown of demographics by year is presented for University C and University B in Table 16 and Table 17, respectively. Participants who answered "other", "prefer not to respond", or "not sure" to the demographic questions were placed in the "No Response/Other" category along with students of whom this data was not gathered. These participants were excluded from analysis dealing directly with that particular demographic. The exception is participants who indicated "Other" as their race, but in the provided text box stated they were of a particular descent (i.e. English, Indian, etc.). Also, students who did not identify as a particular race but did identify as Hispanic/Latino are characterized as under-represented minorities.

Table 16. University C Longitudinal Participants

Demographics		Data Collection Point			
		Freshman		Sophomore	Senior
		Pre-Course[a,b]	Post- Course		
Sex	Male	1203	1326	264	76
	Female	359	391	87	34
	Other[c]	111	8	2	1
Under-Represented Minority	Yes	271	298	64	16
	No	1292	1422	287	94
	No Response	110	5	2	1
1st Generation Student	Yes	246	219	35	14
	No	1315	1169	208	72
	No Response[d]	112	337	110	25
	Total:	**1673**	**1725**	**353**	**111**

Notes: [a] Pre-course data was not taken from students in the Freshman course during the first semester of data collection, Fall 2015.
[d] Demographic data was not collected in the Freshman pre-course survey. If the participant did not complete any other survey, demographic data was not recorded.
[c] Participants who selected "Prefer not to respond" at any point during the study were placed in this category, regardless if another answer was provided later.
[d] Data on parent/guardian education was not collected during the first semester of data collection, Fall 2015

Table 17. University B Longitudinal Participants

Demographics		Data Collection Point			
		Freshman	Sophomore	Junior	Senior
Sex	Male	124	91	69	39
	Female	37	28	23	15
	Other/No Response[a]	6	2	2	1
Under-Represented Minority	Yes	25	17	11	8
	No	132	101	80	45
	No Response	10	3	3	2
1st Generation Student	Yes	5	10	13	7
	No	69	97	79	48
	No Response[b]	93	14	2	0
	Total:	**167**	**121**	**94**	**55**

Notes:	[a] Participants who selected "Prefer not to respond" at any point during the study were placed in this category, regardless if another answer was provided later. [b] Data on parent/guardian education was not collected from Cohort 1 as Freshmen.

7.1.1 Differences in Engineering Design Self-Efficacy and GPA by Demographic Each Year

The results of t-tests for each lens of the engineering design self-efficacy survey for each demographic at each data collection point can be seen in full in Appendix B. An overview of the significant results for each university are presented here.

7.1.1.1 University C Differences by Demographic

The female participants at University C were found to have significantly lower Confidence, Motivation, and Expectation of Success and a higher Anxiety during both the pre-course and post-course freshman data points. At the sophomore data point, the female participants were found to have significantly lower motivation and higher anxiety than their male counterparts. No significant differences were seen between female and male participants at the senior data collection point. No significant differences were ever found in average GPA between female and male participants.

Participants who identified as under-represented minorities were found to have significantly higher motivation to conduct engineering design at the pre-course freshman data point. At the post-course freshman data point, under-represented minorities were found to have higher confidence, but also a higher anxiety for conducting engineering design. Additionally, at the end of their first year, Under-represented minorities were found to have a significantly lower average GPA. This significantly lower average GPA was also seen after the student's second year.

First-generation college students were found to have a significantly higher expectation of success for conducting engineering design when compared to their classmates at the pre-course freshman data point, but were also found to have significantly higher anxiety. At the post-course freshman data point, first-generation students were again found to have higher anxiety. No additional differences were found during the sophomore or senior data points.

Overall, many statistically significant differences were noted between demographic early in the mechanical engineering curriculum, but by the senior year, there were no significant differences between the groups.

7.1.1.2 University B by demographic differences

During the freshman-year data collection point, female participants at JMU were found to have significantly lower confidence and expectation of success for conducting engineering design when compared to their male counterparts. This significantly lower confidence and expectation of success was also noted at the sophomore year data collection point. However, there were no statistically significant differences found between female and male participants during the junior or senior years.

Participants at JMU who identified as under-represented minorities were found to have a significantly lower anxiety for conducting engineering design during their sophomore year, but no other significant differences were found based on race or ethnicity. Unfortunately, there were too few first-generation college students at JMU to perform any statistical analyses on their engineering design self-efficacy. Throughout the entire study at JMU, no significant differences were found for average GPAs based on any demographic factor.

7.2 Proportion of Participants Voluntarily Involved in Makerspaces by Demographic

Chi-squared tests on proportions were used to evaluate whether or the proportions of students with different demographics who were voluntarily involved in an academic makerspace were significantly different. While the proportion data may include all three levels of involvement (No Involvement, Class-Only Involvement, and Voluntary Involvement), all statistical analyses were conducted on the binary factor of whether or not the students were voluntarily involved. Thus, students in the No Involvement and Class-Only Involvement groups were combined into a Not Voluntarily Involved group.

7.2.1 University C Proportions of Voluntarily Involved Participants by Demographics

The proportions of participants at each involvement level for each demographic can be seen in Table 7, Table 19, Table 20, and Table 21. The results of the chi-squared tests of proportions can be seen in Table 22. Female participants were found to have a statistically significant lower proportion of voluntarily involved individuals when compared to their male counter parts at all four data collection points. Under-represented minorities were found to have a significantly lower proportion of participants voluntarily involved in the makerspace at the freshman post-course data point, and first-generation college students were found to have a lower proportion at the freshman pre-course data point. After these early data points, neither group had significantly lower proportions than their counterparts.

Table 18. University C, Freshman Pre-course Involvement Level by Demographics

Involvement Level	Total	Male	Female	URM	Non-URM	1st Gen	Non-1st Gen
Voluntary	20.0%	22.1%	12.5%	19.2%	19.9%	14.6%	20.6%
Class-Only	5.5%	5.7%	5.3%	4.8%	5.7%	4.5%	5.8%
No Involvement	74.5%	72.2%	82.2%	76.0%	74.4%	80.9%	73.6%
Total	**1673**	**1203**	**359**	**271**	**1292**	**246**	**1315**

Table 19. University C, Freshman Post-course Involvement Level by Demographics

Involvement Level	Total	Male	Female	URM	Non-URM	1st Gen	Non-1st Gen
Voluntary	34.1%	35.5%	28.6%	28.5%	35.3%	30.6%	35.9%
Class-Only	14.1%	14.2%	14.3%	13.1%	14.3%	13.2%	15.1%
No Involvement	51.8%	50.3%	57.0%	58.4%	50.4%	56.2%	48.9%
Total	**1725**	**1326**	**391**	**298**	**1422**	**219**	**1169**

Table 20. University C, Sophomore Involvement Level by Demographics

Involvement Level	Total	Male	Female	URM	Non-URM	1st Gen	Non-1st Gen
Voluntary	53.3%	58.0%	37.9%	54.7%	52.6%	40.0%	53.8%
Class-Only	26.3%	24.2%	33.3%	29.7%	25.8%	40.0%	26.9%
No Involvement	20.4%	17.8%	28.7%	15.6%	21.6%	20.0%	19.2%
Total	**353**	**264**	**87**	**64**	**287**	**35**	**208**

Table 21. University C, Involvement Level by Demographics

Involvement Level	Total	Male	Female	URM	Non-URM	1st Gen	Non-1st Gen
Voluntary	67.6%	76.3%	47.1%	56.3%	69.1%	64.3%	66.7%
Class-Only	22.5%	11.8%	47.1%	31.3%	21.3%	21.4%	23.6%
No Involvement	9.9%	11.8%	5.9%	12.5%	9.6%	14.3%	9.7%
Total	**111**	**76**	**34**	**16**	**94**	**14**	**72**

Table 22. University C Results of Chi-squared Tests for Proportions for Demographics

Freshman, Pre-Course			
Demographic	**χ^2**	**df**	**p**
Sex	15.31	1	<0.001‡
URM	0.033	1	0.857
1st Gen	4.31	1	0.038†
Freshman, Post-Course			
Demographic	**χ^2**	**df**	**p**
Sex	6.06	1	0.014†
URM	4.74	1	0.029†
1st Gen	2.08	1	0.150
Sophomore			
Demographic	**χ^2**	**df**	**p**
Sex	9.74	1	0.0018‡
URM	0.026	1	0.871
1st Gen	1.78	1	0.182
Senior			
Demographic	**χ^2**	**df**	**p**
Sex	7.85	1	0.0051‡
URM	0.530	1	0.466
1st Gen	0.00	1	1.00

*Significant at α=0.10, †Significant at α=0.05, ‡Significant at α=0.01

7.2.2 Proportions of Voluntarily Involved Participants by Demographics at University B

The proportions of participants at each involvement level for each demographic can be seen in Table 23, Table 24, and Table 25. The results of the chi-squared tests of proportions can be seen in Table 26. At no point during data collection did any demographic have a lower proportion of students voluntarily involved.

Table 23. University B, Sophomore Involvement Level by Demographics

Involvement Level	**Total**	**Male**	**Female**	**URM**	**Non-URM**	**1st Gen**	**Non-1st Gen**
Voluntary	28.1%	27.5%	28.6%	23.5%	27.7%	40.0%	29.9%
Class-Only	71.9%	72.5%	71.4%	76.5%	72.3%	60.0%	70.1%
Total	**121**	**91**	**28**	**17**	**101**	**10**	**97**

Table 24. University B, Junior Involvement Level by Demographics

Involvement Level	Total	Male	Female	URM	Non-URM	1st Gen	Non-1st Gen
Voluntary	56.4%	57.1%	50.0%	36.4%	57.5%	53.8%	56.4%
Class-Only	43.6%	42.9%	50.0%	63.6%	42.5%	46.2%	43.6%
Total	**94**	**70**	**22**	**11**	**80**	**13**	**78**

Table 25. University B, Senior Level by Demographics

Involvement Level	Total	Male	Female	URM	Non-URM	1st Gen	Non-1st Gen
Voluntary	80.4%	81.0%	76.9%	100%	76.1%	66.7%	83.0%
Class-Only	19.6%	19.0%	23.1%	0.0%	23.9%	33.3%	17.0%
Total	**56**	**42**	**13**	**8**	**46**	**9**	**47**

Table 26. University B, Results of Chi-squared Tests for Proportions for Demographics

Sophomore			
Demographic	χ^2	**df**	**p**
Sex	0.013	1	0.910
URM	0.042	1	0.838
1st Gen	0.434	1	0.510
Junior			
Demographic	χ^2	**df**	**p**
Sex	0.346	1	0.557
URM	0.455	1	0.500
1st Gen	0.030	1	0.863
Senior			
Demographic	χ^2	**df**	**p**
Sex	0.101	1	0.751
URM	0.571	1	0.450
1st Gen	1.27	1	0.259

*Significant at α=0.10, †Significant at α=0.05, ‡Significant at α=0.01

7.3 Impacts of Makerspace Involvement on Engineering Design Self-Efficacy and GPA

7.3.1 Comparisons between levels of Makerspace Involvement at University C

The average EDSE scores for each involvement level at University C can be seen for each data collection point in Figure 19, Figure 20, Figure 21, and Figure 22 with their corresponding ANOVA tests in Table 27, Table 28, Table 29, and Table 30, respectively. Involvement is correlated to higher self-efficacy throughout the study. Both Freshman-level data points find Voluntarily Involved students to have significantly higher Confidence, Motivation, and Expectation of Success and significantly lower Anxiety than both the No Involvement participants and the Class-Only Involvement participants.

At the sophomore data collection, Voluntarily Involved students still have significantly better averages than the No Involvement students in all four lenses of the EDSE metric. At this point, the Class-Only Involvement group also a statistically significant advantage over the No Involvement group in terms of Confidence to conduct engineering design tasks while the Voluntarily Involved group only maintains an advantage over the Class-Only Involvement in Anxiety, where the Voluntary group has a significantly lower average.

At the senior-level data point, the Voluntarily Involved and Class-Only Involvement Groups both have significantly lower Anxiety than the No Involvement group. However, there are no statically significant difference between the Voluntarily Involved and Class-Only Involved groups at the senior level.

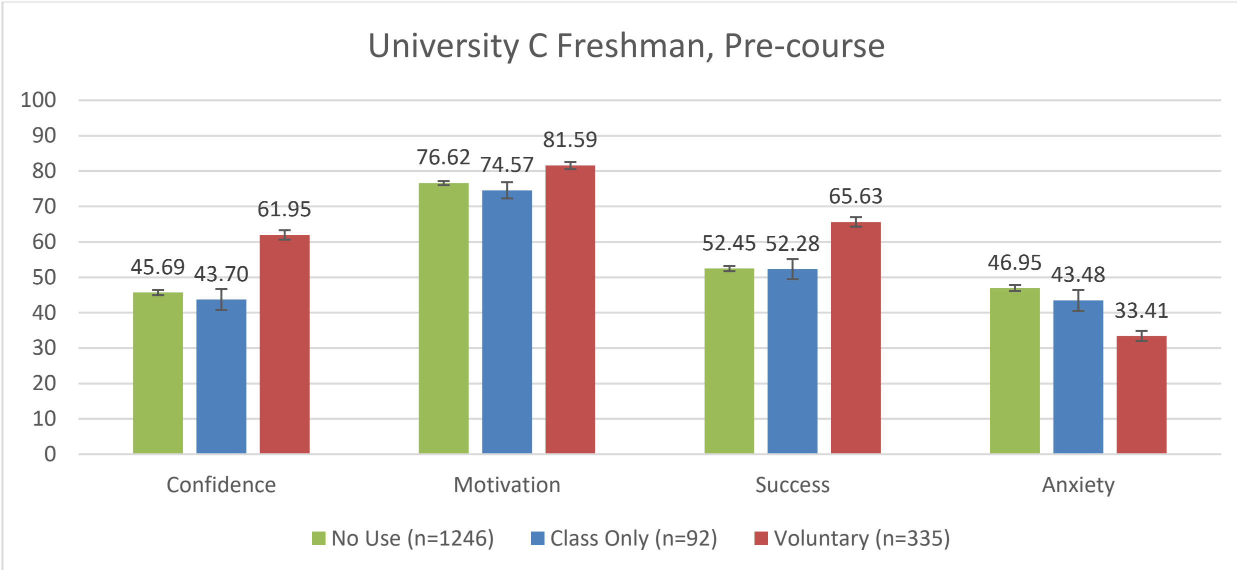


Figure 19. University C Freshman Pre-Course EDSE based on Involvement Level

Table 27. University C Pre-course Freshman ANOVA on EDSE by Involvement Level

One-way ANOVA Results					Tukey Post-hoc Comparisons		
Confidence							
Involvement	**F**	**df_1**	**df_2**	**p**	**Pairwise Comparison**	**Adj. p**	**d**
No Involvement					Class-None	0.77	
Class Only	50.2	2	1669	<0.001‡	Voluntary-None	<0.001‡	0.589
Voluntary					Voluntary-Class	<0.001‡	0.661
Motivation							
Involvement	**F**	**df_1**	**df_2**	**p**	**Pairwise Comparison**	**Adj. p**	**d**
No Involvement					Class-None	0.609	
Class Only	9.12	2	1669	<0.001‡	Voluntary-None	<0.001‡	0.246
Voluntary					Voluntary-Class	0.008‡	0.348
Expectation of Success							
Involvement	**F**	**df_1**	**df_2**	**p**	**Pairwise Comparison**	**Adj. p**	**d**
No Involvement					Class-None	0.998	
Class Only	33.6	2	1669	<0.001‡	Voluntary-None	<0.001‡	0.491
Voluntary					Voluntary-Class	<0.001‡	0.498
Anxiety							
Involvement	**F**	**df_1**	**df_2**	**p**	**Pairwise Comparison**	**Adj. p**	**d**
No Involvement					Class-None	0.492	
Class Only	30.2	2	1669	<0.001‡	Voluntary-None	<0.001‡	0.471
Voluntary					Voluntary-Class	0.0072	0.350

*Significant at α=0.10, †Significant at α=0.05, ‡Significant at α=0.01
d>0.2 is considered small effect, d>0.5 is considered medium effect, and d>0.8 is considered large effect(Cohen 1988)

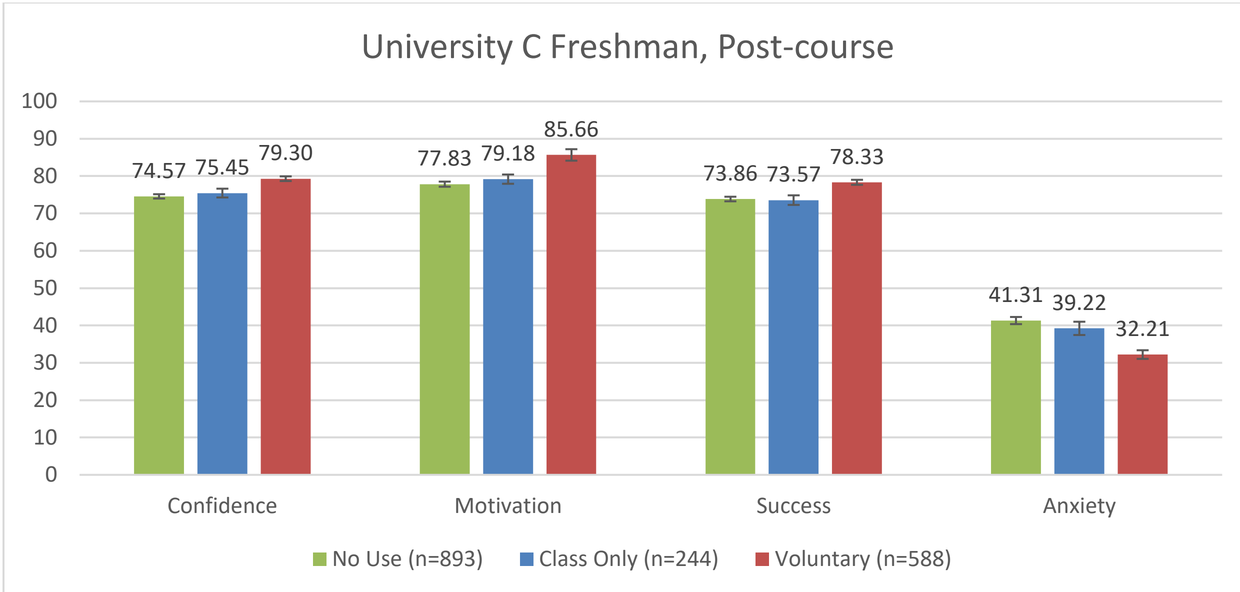


Figure 20. University C Freshman Post-Course EDSE based on Involvement Level

Table 28. University C Post-course Freshman ANOVA on EDSE by Involvement Level

One-way ANOVA Results				**Tukey Post-hoc Comparisons**		
Confidence						
Involvement	**F**	**df$_1$**	**p**	**Pairwise Comparison**	**Adj. p**	**d**
No Involvement				Class-None	0.747	
Class Only	14.4	2	<0.001‡	Voluntary-None	<0.001‡	0.280
Voluntary				Voluntary-Class	0.0075‡	0.227
Motivation						
Involvement	**F**	**df$_1$**	**p**	**Pairwise Comparison**	**Adj. p**	**d**
No Involvement				Class-None	0.774	
Class Only	15.0	2	<0.001‡	Voluntary-None	<0.001‡	0.285
Expectation of Success						
Involvement	**F**	**df$_1$**	**p**	**Pairwise Comparison**	**Adj. p**	**d**
No Involvement				Class-None	0.972	
Class Only	12.5	2	<0.001‡	Voluntary-None	<0.001‡	0.248
Voluntary				Voluntary-Class	0.0014‡	0.265
Anxiety						
Involvement	**F**	**df$_1$**	**p**	**Pairwise Comparison**	**Adj. p**	**d**
No Involvement				Class-None	0.562	
Class Only	18.6	2	<0.001‡	Voluntary-None	<0.001‡	0.319
Voluntary				Voluntary-Class	0.0033‡	0.245

*Significant at α=0.10, †Significant at α=0.05, ‡Significant at α=0.01
d>0.2 is considered small effect, d>0.5 is considered medium effect, and d>0.8 is considered large effect(Cohen 1988)

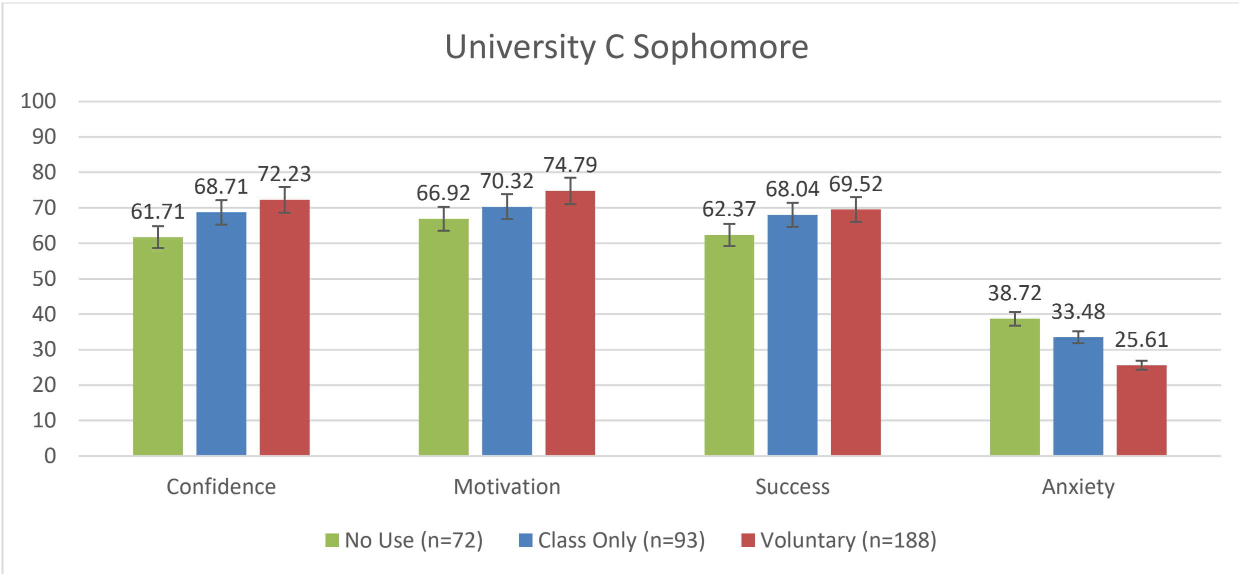


Figure 21. University C Sophomore EDSE based on Involvement Level

Table 29. University C Post-course Freshman ANOVA on EDSE by Involvement Level

One-way ANOVA Results					Tukey Post-hoc Comparisons		
Confidence							
Involvement	**F**	**df₁**	**df₂**	**p**	**Pairwise Comparison**	**Adj. p**	**d**
No Involvement					Class-None	0.035†	0.386
Class Only	9.052	2	348	<0.001‡	Voluntary-None	<0.001‡	0.581
Voluntary					Voluntary-Class	0.260	
Motivation							
Involvement	**F**	**df₁**	**df₂**	**p**	**Pairwise Comparison**	**Adj. p**	**d**
No Involvement					Class-None	0.570	
Class Only	3.895	2	349	0.021†	Voluntary-None	0.023†	0.365
Voluntary					Voluntary-Class	0.227	
Expectation of Success							
Involvement	**F**	**df₁**	**df₂**	**p**	**Pairwise Comparison**	**Adj. p**	**d**
No Involvement					Class-None	0.113	
Class Only	4.117	2	348	0.017†	Voluntary-None	0.012†	0.395
Voluntary					Voluntary-Class	0.794	
Anxiety							
Involvement	**F**	**df₁**	**df₂**	**p**	**Pairwise Comparison**	**Adj. p**	**d**
No Involvement					Class-None	0.448	
Class Only	6.683	2	347	0.0014‡	Voluntary-None	0.0020‡	0.470
Voluntary					Voluntary-Class	0.064*	0.282

*Significant at α=0.10, †Significant at α=0.05, ‡Significant at α=0.01
d>0.2 is considered small effect, d>0.5 is considered medium effect, and d>0.8 is considered large effect(Cohen 1988)

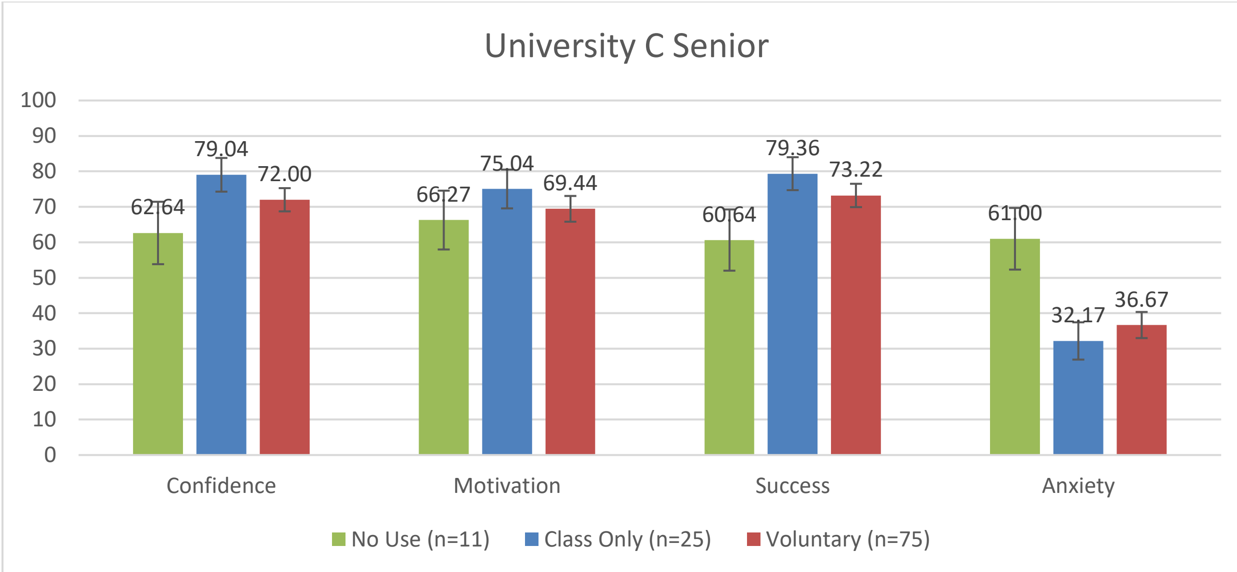


Figure 22. University C Senior EDSE based on Involvement Level

Table 30. University C Post-course Freshman ANOVA on EDSE by Involvement Level

One-way ANOVA Results					Tukey Post-hoc Comparisons		
Confidence							
Involvement	**F**	**df_1**	**df_2**	**p**	**Pairwise Comparison**	**Adj. p**	**d**
No Involvement					Class-None		
Class Only	1.43	2	108	0.245	Voluntary-None		
Voluntary					Voluntary-Class		
Motivation							
Involvement	**F**	**df_1**	**df_2**	**p**	**Pairwise Comparison**	**Adj. p**	**d**
No Involvement					Class-None		
Class Only	0.434	2	108	0.649	Voluntary-None		
Voluntary					Voluntary-Class		
Expectation of Success							
Involvement	**F**	**df_1**	**df_2**	**p**	**Pairwise Comparison**	**Adj. p**	**d**
No Involvement					Class-None		
Class Only	1.79	2	107	0.173	Voluntary-None		
Voluntary					Voluntary-Class		
Anxiety							
Involvement	**F**	**df_1**	**df_2**	**p**	**Pairwise Comparison**	**Adj. p**	**d**
No Involvement					Class-None	0.037†	0.926
Class Only	3.35	2	96	0.039†	Voluntary-None	0.053*	0.782
Voluntary					Voluntary-Class	0.815	

*Significant at α=0.10, †Significant at α=0.05, ‡Significant at α=0.01
d>0.2 is considered small effect, d>0.5 is considered medium effect, and d>0.8 is considered large effect(Cohen 1988)

The average GPA for each involvement group as the students progress through the mechanical engineering curriculum can be seen in Table 31 along with the results of an ANOVA to determine any significant differences. The only statistically significant difference was found at the end of the freshman year where the Class-Only Involvment group had a significantly higher GPA than the No Involvement group as determined by a Tukey post-hoc test (adj. p = 0.074, d=0.47). The Voluntarily Involved group was not found to significantly difference from either the No Involvement group (adj. p = 0.233) or the Class-Only group (adj. p = 0.622).

Table 31. Average GPA for Involvement Groups for Each Year at University C.

Freshman GPA						
Involvement	**n**	**Average**	**F**	**df_1**	**df_2**	**p**
No Involvement	122	3.395				
Class Only	26	3.598	3.06	2	207	0.0499†
Voluntary	61	3.505				
Sophomore GPA						
Involvement	**n**	**Average**	**F**	**df_1**	**df_2**	**p**
No Involvement	40	3.389				
Class Only	41	3.398	0.012	2	158	0.943
Voluntary	78	3.411				
Senior GPA						
Involvement	**n**	**Average**	**F**	**df_1**	**df_2**	**p**
No Involvement	1	3.390				
Class Only	6	3.497	0.036	2	16	0.965
Voluntary	12	3.472				

*Significant at α=0.10, †Significant at α=0.05, ‡Significant at α=0.01
d>0.2 is considered small effect, d>0.5 is considered medium effect, and
d>0.8 is considered large effect(Cohen 1988)

7.3.2 Comparisons between Levels of Makerspace Involvement at University B

The average EDSE scores for each involvement level at University C can be seen for each data collection point in Figure 23, Figure 24, and Figure 25. The results of the t-tests comparing the groups at each stage can be found in Table 32. During the sophomore year, students who were voluntarily involved were found to have significantly higher Confidence, Motivation, and Expectation of Success along with a significantly lower Anxiety.

While there was no statistically significant difference found during the junior year, the Voluntary users during the senior data collection were found to have higher Confidence and lower Anxiety when conducting engineering design. In this regard, at both universities, there seems to be an advantage to early involvement that dissipates the further the students' progress into the engineering curriculum.

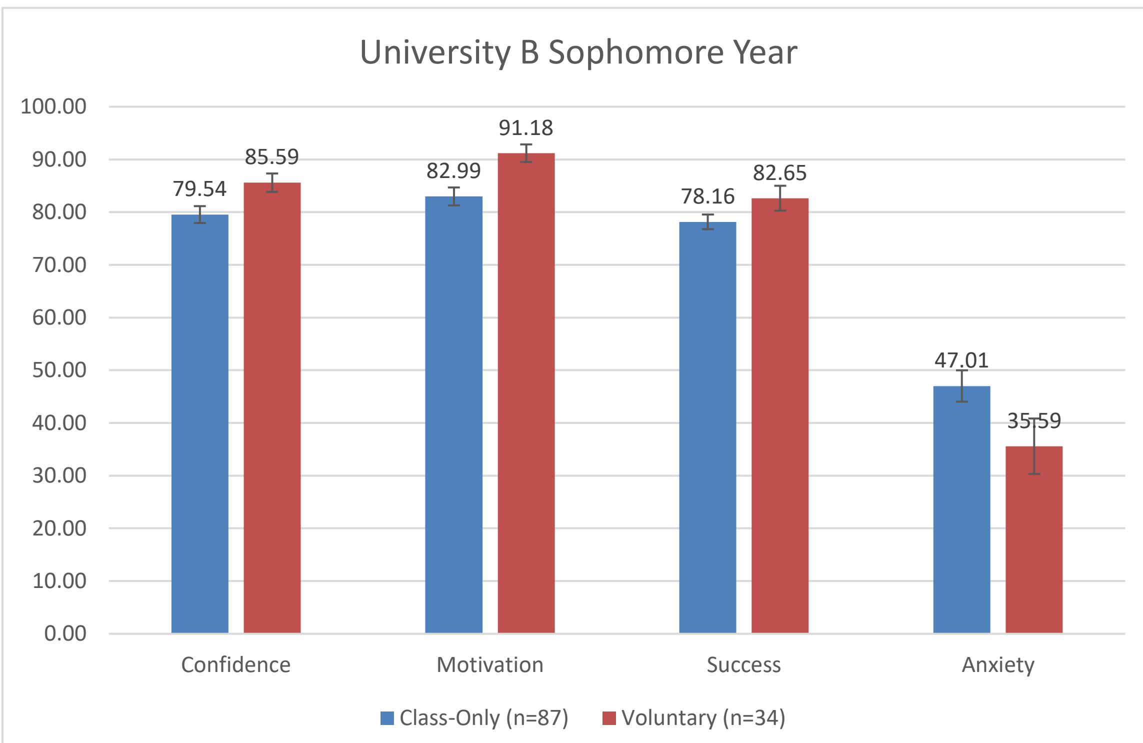


Figure 23. University B EDSE based on Sophomore Involvement Level

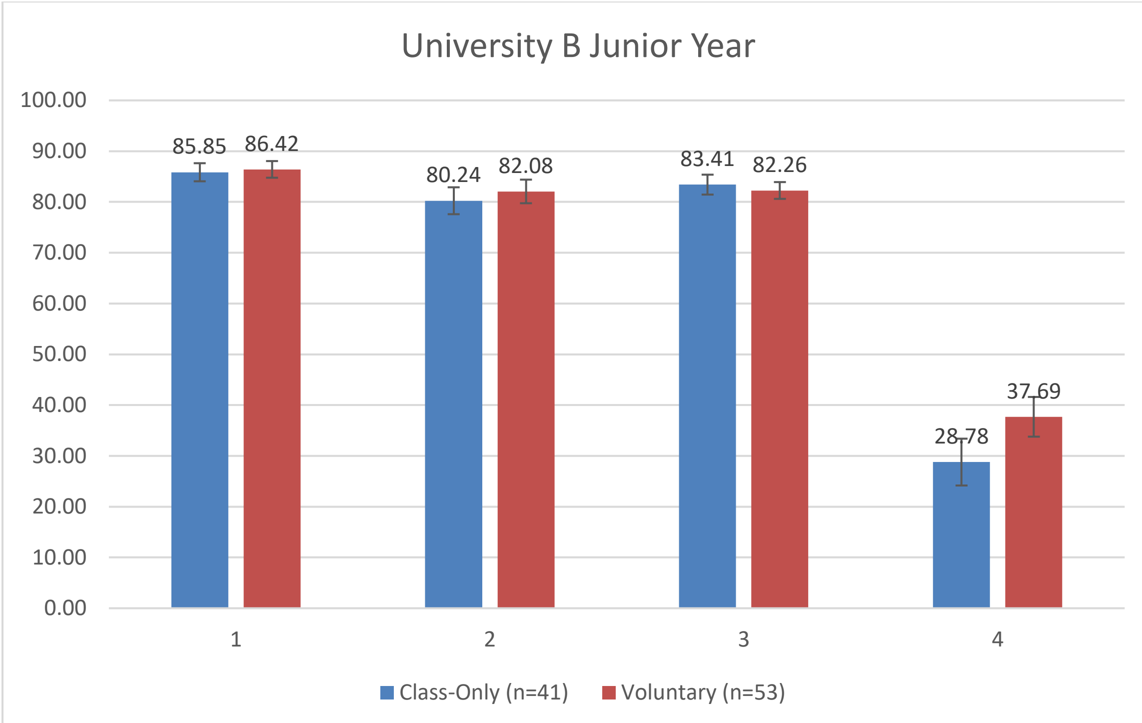


Figure 24. University B EDSE based on Junior Involvement Level

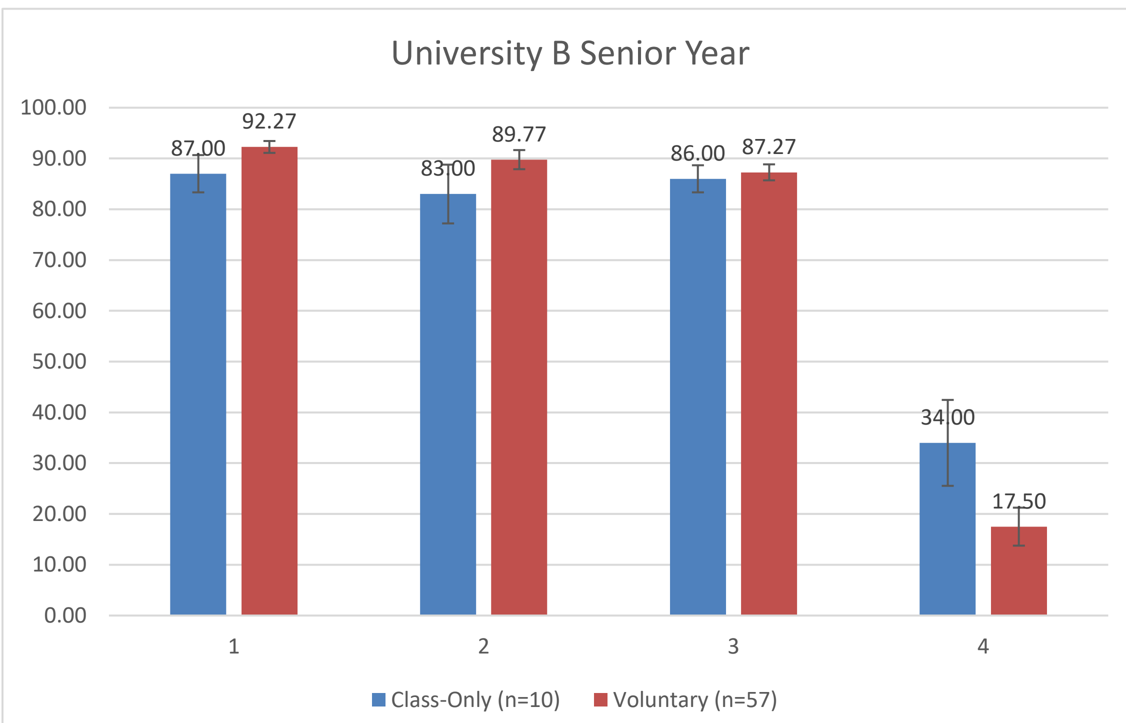


Figure 25. University B EDSE based on Senior Involvement Level

Table 32 Summary of t-tests for Involvement Groups' EDSE at University B

Sophomore			
Metric	**t**	**df**	**P**
Confidence	2.17	119	0.032†
Motivation	2.81	119	0.0059‡
Success	1.68	119	0.096*
Anxiety	1.98	119	0.051*
Junior			
Metric	**t**	**df**	**p**
Confidence	0.231	92	0.818
Motivation	0.520	92	0.604
Success	0.451	92	0.653
Anxiety	1.47	91	0.144
Senior			
Metric	**t**	**df**	**p**
Confidence	1.76	52	0.083*
Motivation	1.41	52	0.163
Success	0.359	52	0.721
Anxiety	1.87	52	0.067*

*Significant at α=0.10, †Significant at α=0.05, ‡Significant at α=0.01

The average GPA for each group can be found in Table 33 along with summaries of the t-tests analyzing whether or not they are significantly different. It was found that students who are voluntarily involved during their sophomore year had significantly higher GPAs than students who only used the makerspace for mandatory classes. However, that benefit does not benefit past the sophomore year.

Table 33 Summary of t-tests for Involvement Groups' GPA at University B

Involvement	n	Average	t	df	p
Sophomore GPA					
Class Only	62	2.790	1.68	81	0.096*
Voluntary	22	2.976			
Junior GPA					
Class Only	41	2.980	0.541	92	0.59
Voluntary	53	3.020			
Senior GPA					
Class Only	11	3.000	1.23	54	0.226
Voluntary	45	3.132			

*Significant at α=0.10

7.4 Encouraging Involvement through Early Exposure

In the freshman-level course at University C used for data collection in this study, there is a 3D modeling project. Some of the professors who teach the course have begun having their students use resources available in an academic makerspace to make a 3D print of their project. Seeing this innovation, other professors have begun using a large-batch 3D printer to print the models for the students to be measured and turned in with their final report. It should be noted that, while the students received a part, they were not required to go to the makerspace themselves. Lastly, some sections of the course did not provide a 3D printed model with this project. The students from each group will be henceforth referred to as the Self Print group, the Group Print group, and the No Print group. Students from each group were analyzed to determine if this project may impact future involvement. A visual representation of the proportions of participants who become voluntarily involved is show for each year in Figure 26, Figure 27, and Figure 28. Table 34 shows the results of the chi-squared tests.

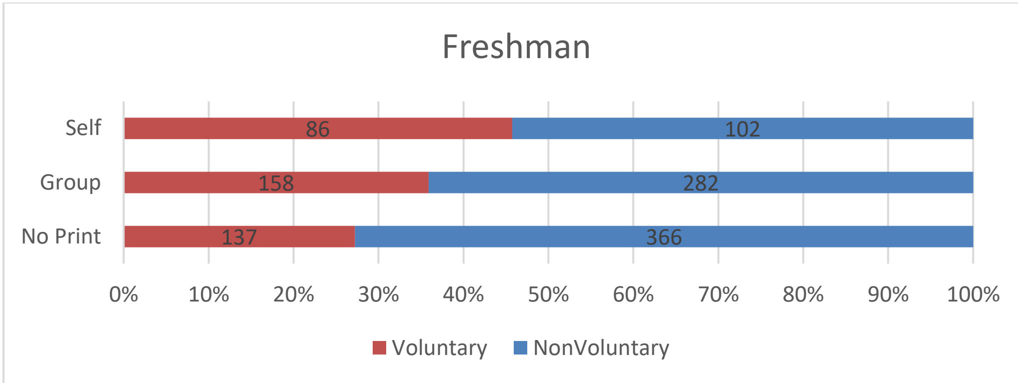


Figure 26. Proportion of Voluntarily Involved Students as Freshman based on a Freshman-level project

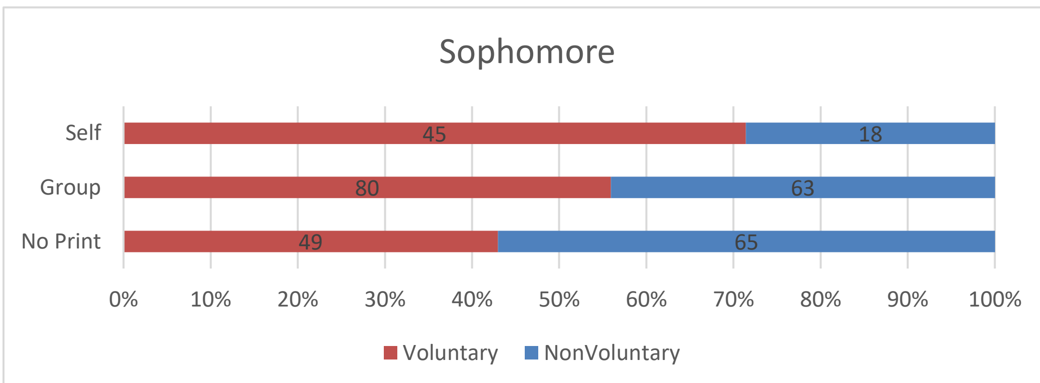


Figure 27. Proportion of Voluntarily Involved Students as Sophomore based on a Freshman-level project

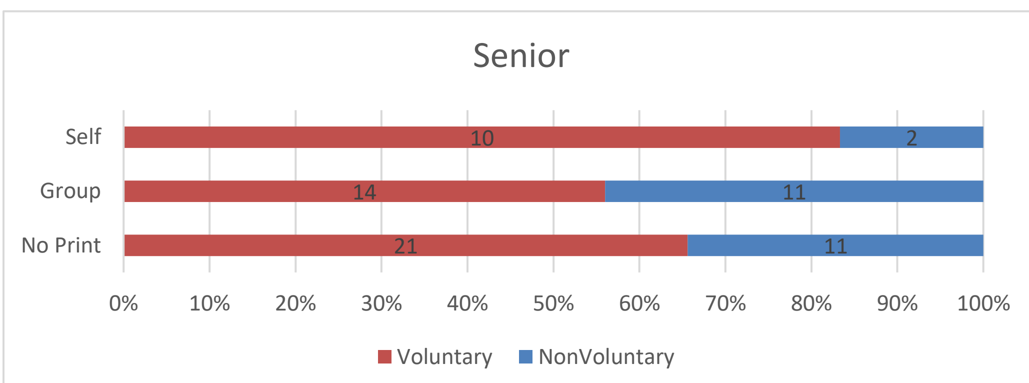


Figure 28. Proportion of Voluntarily Involved Students as Senior based on a Freshman-level project

Table 34 Chi-squared tests for proportions of Voluntarily Involved Students from each print Group

Chi-squared Test on All Groups				Post-hoc Chi-Squared tests on Pairs			
Freshman							
Project Group	**χ2**	**df**	**p**	**Pairwise Comparison**	**χ2**	**df**	**p**
Self-Print				Self & Group	8.21	1	0.0042‡
Group Print	22.58	2	<0.001‡	Self & No Print	21.45	1	<0.001‡
No Print				Group & No Print	5.36	1	0.021†
Sophomore							
Project Group	**χ2**	**df**	**p**	**Pairwise Comparison**	**χ2**	**df**	**p**
Self-Print				Self & Group	4.26	1	0.039†
Group Print	13.49	2	0.0012†	Self & No Print	13.18	1	<0.001‡
No Print				Group & No Print	4.39	1	0.036†
Senior							
Project Group	**χ2**	**df**	**p**	**Pairwise Comparison**	**χ2**	**df**	**p**
Self-Print				Self & Group			
Group Print	2.67	2	0.197	Self & No Print			
No Print				Group & No Print			

*Significant at $\alpha=0.10$, †Significant at $\alpha=0.05$, ‡Significant at $\alpha=0.01$
d>0.2 is considered small effect, d>0.5 is considered medium effect, and d>0.8 is considered large effect(Cohen 1988)

The group of students who printed the project themselves were found to have a significantly higher proportion of studetns become voluntarily involved by the end of the freshman semester when compared to both of the other print groups. Furthermore, these students were also more likely to be involved by their sophomore year.

It was also found that the group print students were significantly more likely to be voluntarily involved that the students who did not have a 3D print included in their project. This higher proportion was also seen of students in the sophomore course. This suggests that while the self-print project is best for encouraging voluntary involvement in an academic makerspace, having parts printed for the students may still motivate them to become involved.

7.5 Retention

A portion of the study participants were analyzed for retention at University C. This was done by observing 165 students who did not fill out a makerspace survey past their sophomore year and collecting data on their current major. Of those 165 students, 12 changed their major to something other than mechanical engineering, indicating a 92.7% retention rate in the major for participants in or study, which matches pretty closely the college records for the entire major.

To see if involvement in an academic makerspace may have influenced students to remain in the mechanical engineering major, a chi-squared test on proportions test was conducted to compare the retention rates of students who were voluntarily involved to those who were not. While makerspace involvement is believed to encourage involvement, the chi squared tests were not able to determine a statistically significant difference in retention rates. This may be due to the very high retention rates University C already has. The results of the chi-squared tests for students voluntarily involved in their freshman and sophomore years can be seen in Table 35 and Table 36, respectively.

Table 35. Proportion of Freshman Voluntarily Involved in makerspace that changed majors

	Total	Changed Major	**χ2**	**df**	**p**
Voluntarily Involved (Freshman)	50	1 (2%)	1.94	1	0.163
Not Voluntarily Involved	115	11 (9.6%)			

Table 36. Proportion of Sophomore Voluntarily Involved in makerspace that changed majors

	Total	Changed Major	**χ2**	**df**	**p**
Voluntarily Involved (Sophomore)	64	1 (1.04%)	0.186	1	0.667
Not Voluntarily Involved	69	3 (3.13%)			

CHAPTER 8. CONCLUSIONS

This dissertation presents two avenues for assisting engineers in developing their early-stage design skill, perspective sketching, and participation in a makerspace. Only six weeks of course time spent on perspective sketching effectively improves free-hand sketching skills while also improving spatial visualization skills. The current work observes similar gains in spatial visualization skills for both perspective sketching and a more traditional engineering approach. Makerspaces are another avenue for developing early-stage design skills. Statistically significant correlations are observed between students' motivation to do design and their involvement in makerspaces. Their experiences prior to entering the university also influence their decision to become involved. This dissertation demonstrates one approach for increasing student engagement early in their undergraduate careers through a simple 3d printer project requiring the students to use the makerspace.

8.1 Sketching Study

This dissertation demonstrates sketching is one of the easiest methods to implement in engineering curricula to improve students' spatial visualization skills while they gain other incredibly useful skills for engineering. With the evidence from literature that spatial visualization is a key factor in success for many aspects of engineering (Pleck 1991, Ferguson 1994) and the extensive work by Sorby (Sorby and Baartmans 2000, Sorby 2009, Sorby and Veurink 2010, Sorby, Casey et al. 2013) indicating that improved spatial visualization increases retention, there is almost no reason not to include sketching in every engineering program attempting to develop successful engineers with skills crucial for understanding and tackling complex problems.

Furthermore, the data presented in this dissertation suggest that more universities should consider teaching their engineering students more advanced sketching techniques as they have been shown to improve spatial visualization score just as effectively as more traditional methods but with the added benefit of more effectively improving students' sketching ability.

The more advanced sketching techniques evaluated in this dissertation and typically found in industrial design courses include sketching in perspective and using ray-tracing to include shadows cast by the object. To evaluate the impact of this newer Perspective method has on skills that Traditional engineering sketching curricula have been shown to improve, the spatial visualization skills of two groups of students, one taught each method, were evaluated. The results of the experiment suggest that the Perspective version of the course increased the spatial visualization skills of students as well as the Traditional method. In addition, the Perspective students show significantly greater increases in their free-hand sketching skills. This finding shows that the Perspective method teaches engineering students new, more advanced, sketching skills without taking away from the other skills typically gained through more traditional engineering sketching curricula.

RQ.1) What are the impacts of teaching engineers sketching via an industrial design-based pedagogy?

RQ.1.1) Can a 6-week course in freehand sketching measurably improve engineers' free-hand sketching ability?

A 6-week course in freehand sketching measurably improves engineers' free-hand sketching ability. Six-weeks is enough time to make substantial and important improvements in engineering students' abilities to sketch.

RQ.1.2) Does an industrial design pedagogy for learning free-hand sketching improve spatial visualization as effectively as more traditional engineering drawing pedagogy?

An industrial design pedagogy for learning free-hand sketching improves spatial visualization just as effectively as a more traditional engineering drawing pedagogy. This provides new avenues for increasing the skills engineering students are developing without requiring additional course time.

RQ.1.3) How are spatial visualization skills impacted during a freshman-level course on sketching and computer-aided modeling?

Practice on both sketching and with computer-aided modeling improves spatial visualization skills.

8.1.1 *Limitations of sketching study*

There are two major limitations of the sketching study. The first was that the traditional method was only taught by one instructor, and this instructor did not teach the perspective method in any of his sections. Due to this, any differences between the two groups could be attributed to the instructor and not the method. Future work could include one of the instructors teaching the alternative method to ensure it is due solely to the method used. The second limitation is that both versions of the class follow the same curriculum for the CAD portion of the class. While the additional data point immediately after the sketching portion of the class helped determine the sketching portion of the course improved spatial visualization, a true test of whether CAD or sketching improves these skills more effectively would need to include a class where CAD was taught before sketching ot sketching was not taught at all. Given the many stated benefits of teaching sketching in engineering, this type of experiment would be best suited for a university that does not currently teach sketching in their curriculum, but have aspirations to include it. Additionally, taking the spatial visualization tests multiple times could lead to a practice effect, which may result in bias results.

8.2 Future Work on Sketching

Sketching is a critical early phase skill for engineers, and much more work needs to be undertaken in this area. This dissertation illustrated just one effective approach for teaching engineers how to sketch. Future work needs to evaluate the various approaches for teaching sketching. Additional work is also needed to identify the critical sketching skills that engineers need. For example, it may be very important for engineers to be able to free-hand sketch and to draw the different views and sides of an object, but having it in two-point perspective may not be critical. Shading and shadows may be important knowledge for creating refined CAD images that make a model look almost like a real product or learning to do this step by hand may not be important. The evaluation of sketch quality also needs to be more refined with a scale with greater detail and more than just overall sketch quality being evaluated. Line quality, perspective accuracy, and many other dimensions of sketch quality should be evaluated and validated against expert assessment. Ideally, computer software would be developed to automatically evaluate the sketch quality for the camera quiz question.

8.3 Makerspaces

As makerspaces have become more and more popular on university campuses, particularly with connections to engineering programs, it is crucial that their impact is measured and understood. This paper has shown empirical evidence that involvement in an academic makerspace is positively correlated to superior engineering design self-efficacy. At University A and University C, students who chose to spend time in an academic makerspace were found to have significantly higher Confidence, Motivation, and Expectation of Success than students with no involvement in a makerspace. At University A and University C, it was also seen that the proportionally fewer female students chose to spend time in an academic makerspace than their male counterparts. Female students at all three Universities were found to have lower self-efficacy in at least one lens when compared to their male counterparts.

Ultimately, the results of this study have shown that students involved in academic makerspaces have a higher self-efficacy for conducting engineering design. This is particularly important due to previous studies showing self-efficacy in a skill being an indicator of success (Hsieh, Sullivan et al. 2012). If we accept the premise that engineering design is the "central or distinguishing activity of engineering" as Dym et al. (Dym, Agogino et al. 2005) summarized from Simon (Simon 1996) and state in the opening of their now famous paper, *Engineering Design Thinking, Teaching, and Learning*, then these results may indicate the revelation of a key method for developing successful engineers. How can we get more students engaged in engineering makerspaces? How can we ensure these spaces are beneficial and inclusive to all students, regardless of gender, ethnicity, or any other demographic?

Of course, as stated above, these results are just the first step in filling the gap on empirical data-driving literature on makerspaces. While correlation is demonstrated, causation is not. Fortunately, additional studies are being carried out to see how students change with longitudinal studies where their involvement may vary semester to semester. These studies may help to understand causation, as well as what factors may lead students to become more involved in an academic makerspace. All of this work will be crucial in understanding the benefits and drawbacks of the inclusion of academic makerspaces in engineering design curriculum.

RQ.2) Makerspaces provide opportunities to increase the amount of prototyping experiences, how do these spaces impact students?

RQ.2.1) Does makerspace involvement improve engineering design self-efficacy?

A positive correlation between involvement and improved engineering design self-efficacy (increased motivation, conference, and expectation of success for design activities along with decreased anxiety for doing design tasks) is observed in the data. This is true for all three of the universities evaluated even though the universities, spaces, and demographics of the students are all very different. The correlations disappear in the upper-level courses, but this could be due to a ceiling effect where after a certain amount of participation in the makerspace, no further benefits to the EDSE are observed.

RQ.2.2) How is makerspace involvement correlated to GPA?

Generally, no correlation to GPA is observed.

RQ.2.3) Does makerspace involvement affect retention in engineering programs?

Retention data is only available for University C and no impact on retention was observed for in major or at the university, but retention rates currently exceed 90% within the major, so observing this will be difficult.

RQ.2.4) What factors influence students to become involved in an academic makerspace?

Students who are highly motivated to do engineering design tend to become involved in makerspaces early in their undergraduate careers. Implementing a 3d printer project in a freshman design course, which requires students to enter the makerspace and print their parts, increases students' later voluntary involvement in the space. Simply having a technician print their 3d designs also increases their makerspace involvement but to a lesser extent.

RQ.2.5) How consistent are the findings on the impacts of makerspaces across three universities?

Findings varied slightly across universities, but there is a consistent trend of makerspace being correlated with higher self-efficacy early on in the curriculum, which may give students a head start in some areas.

RQ.2.6) Are the impacts different for women, underrepresented minorities, and first-generation college students?

Minorities, especially women, are found to be less likely to be involved in these spaces, but the benefits of the space may also be most crucial for engineers from under-represented demographics. The findings in this dissertation encourage future work into improving inclusion in makerspaces.

8.3.1 Limitations of the Makerspace Study

The goal of the longitudinal study was to capture data from the same students from the time they were freshman until seniors in capstone and likely graduating, allowing for causal conclusions to be made. Students at University C are taking longer than expected to graduation, so very few students' data were collected at multiple points. The patterns found in the work's results are only correlational, and causation should not be inferred. Freshman involvement in makerspace data could not be collected at University B since the students had no opportunity to become involved voluntarily before their sophomore year. The sample sizes for URMs are small, and this severely limits the conclusions that can be drawn.

For the cross-section portion of the study, data were taken as a cross-section from each university based on the data available during a calendar year of a longitudinal study. This causes a few limitations on how the data can be analyzed and interpreted. First, as stated in the Discussion, these results cannot show causation between makerspace involvement and engineering design self-efficacy (EDSE). It is possible that students with superior EDSE are themselves more likely to join the space. Second, because each university looks at a different population of students (sophomores and juniors at University B, freshmen, and sophomores at University C), it is not feasible to directly compare students between universities without being affected by significant confounding factors. Finally, the involvement groups used for analysis may be too broad. Qualitative studies, such as those presented by Tomko, Swartz, et al. , (2018), have shown that involvement levels vary greatly student to student. Therefore, having only one level of Voluntary Involvement may result in the neglect of richer data. Regression analysis and other indicates of involvement levels have been explored, but none have led to useful insights beyond what is presented in this dissertation (Hilton, MacMullan et al. 2020).

8.4 Future Work on Makerspaces

Makerspaces are a rather new phenomenon in engineering education, and much work is needed to understand their impacts, how best to engage students in the space, what is learned by the students, how do you minimize barriers for participation and much more. Much future work is still needed to have an empirical basis for determining the impacts of university makerspaces. This dissertation evaluated only a very small number of factors and outcomes. Ideally, the current study would be follow-up with a much larger, multi-university study to see how variations in makerspaces, students, and university characteristics affect the outcomes. More investigation is needed into the effects of University B's makerspace where after a certain point, more involvement did not change the outcomes, and women students had the same outcomes as men. Can similar observations be made for women of similar involvement levels at other universities? Is the influence instead due to the relatively high number of women faculty in their engineering program? As the positive impacts of makerspaces are better documented, then the question becomes how can you reduce the barriers to participation? The work illustrated one path for getting students involved in the makerspaces. Many other approaches likely exist, and many other factors likely influence a students' engagement.

8.5 Contributions

This dissertation makes important contributions to developing engineers' early-stage design skills.

- This work identified a six-week course in perspective sketching as being an effective approach for developing the critical prototyping, idea generation, and communication skill of being able to free-hand sketch.
- Perspective sketching is also shown to be as effective as a more traditional approach to engineering drawing for developing spatial reasoning skills. Spatial reasoning skills strongly correlate with performance in later engineering classes and retention in engineering.
- Empirical evidence demonstrating correlation between EDSE and early student involvement in university makerspaces is provided.
- Factors that influence students' involvement in university makerspaces were documented, including factors that could be controlled by instructors to encourage participation in academic makerspaces.
- Evaluation if makerspace involvement effects GPA or retention and the limited data presented show no impact for GPA or retention, but the retention rate was already over 90%, meaning statistically significant changes are hard to detect.
- One effective method for encouraging student participation in makerspaces was identified and is to include a 3d print project in a freshman design course.

APPENDIX A. UNDERSTANDING THE PROTOTYPING ABILITIES OF EXPERIENCED DESIGNERS

The following study investigated experienced designers as they carried out a design of a system that required the heavy use of prototyping. The findings of this study helped inspire some of the research questions for the two studies presented in this dissertation. The goal of including this appendix is to give light to the motivations behind the overall dissertation.

A.1 Introduction

In order to for engineering students to be successful designers, they need to learn effective design processes and practices to complete their technical skills. Included in these skills sets are strategies for effective prototyping that maximize the knowledge and design confidence gained while minimizing cost and time. Unfortunately, few studies provide highly detailed accounts of the prototyping strategies employed by highly innovative design teams. The lead authors of this paper were provided access to a team of designers that have made significant inroads to reducing the installation costs of solar panels. Through structured follow-up interviews, details account of the prototypes and their purposes was obtained from the designers. Some intriguing outcomes and potential strategies for students were obtained.

A.2 Background

A.2.1 Prototyping Strategies

Prototypes are powerful tools in the process of designing a new product. They allow for the designers to strengthen their mental models of how a design will look and behave (Viswanathan, Atilola et al. 2014), effectively share ideas with other designers (Goldschmidt 2007) and provide a medium for validating or improving design decisions (Otto and Wood 2001). Prototypes have the ability to reveal shortcomings that may not be detectable by other methods (Viswanathan, Atilola et al. 2014, Horton and Radcliffe 1995, Ward, et al. 2012, Viswanathan and Linsey 2013). However, there are potential problems that can occur as a result of using prototypes. Due to the money, effort, and time spent on materials and fabrication of prototypes, design fixation can occur as a part of the "Sunk Cost Effect" (Viswanathan and Linsey 2013). This theory states that the more resources expended on a certain path, the less likely a designer will be to move on to a new idea. Design fixation and other shortcomings in the use of prototypes can be mitigated through strategy in the construction of prototypes (Dow, et al. 2010, Camburn, et al. 2013). It has also been observed that more experienced designers are more successful in mitigating design fixation (Viswanathan and Linsey 2013).

While experts are better at mitigating fixation, physical prototypes have been found to help students overcome design fixation. Viswanathan (2012) performed an experiment in which students were given a flawed prototype and asked to construct a more effective design. The participants fixated on the flawed design at first. However, the participants were able to quickly overcome their initial fixation through testing a rebuilding the prototypes. This shows that while prototypes can cause fixation, they can also be used to overcome it. Therefore, it is important for students to learn effective prototyping strategies.

In a previous study, Viswanathan, Atiola, et al. (2014) found that professional designers would purposefully implement strategies specifically geared towards avoiding shortcomings such as the "Sunk Cost Effect". This paper looks to build off of the work done by Viswanathan, Atiola, et al. (2014) by using more qualitative research methods to look specifically at what strategies were used and why they were implemented.

A.2.2 Classifications

Several classification systems have been created by researchers as they study prototypes. These classifications often characterize both the intent of the prototype, such as performing evaluations or communicating aesthetics (Eggert 2005), and the physical characteristics, such as the scale or the material used to create prototype (Michaelraj 2009). Gaining a better understanding of these characteristics improves the researchers' ability to record, analyze, and discuss data collected during the study of prototypes (Hess 2012). The classification system defines both the intended use of the prototype as well as its physical characteristics. The classifications developed are shown in Table A1.

This classification system was divided up into different sections used to describe the overall prototype. An extensive literature review of past efforts in prototype taxonomy was conducted and used to determine the needed categories and categories available in each section. The first section was the overall Purpose of the prototype. The purpose of the prototype defines how the prototype was used by the designers. Ulrich and Eppinger (2004) suggest that prototypes can have four major purposes: learning, communication, integration, and milestones. However, through the data collection in the previous work on this project, Viswanathan, Atiola, et al. (2014) found that the designers on the SIMPLE

BoS project had an informal taxonomy system to describe the purpose of a prototype: Design Intent, Functional, or Representation. The categories used for this classification system were based on the designers' current system as this allowed them to classify each prototype more easily during data collection. Adjustments were made based on literature to include other aspects not represented by this taxonomy and represent the clear differences between each category.

The Design Intent category describes a prototype used to communicate to other designers on a project how the product should look and/or operate. Communication is one of the major purposes behind creating a prototype as it allows all stakeholders in a project

Table A1 Prototype Classifications

Purpose-*Why is this prototype being created?*	
Design Intent	Used to convey design intent.
Functional	Used for functional tests (see below).
Integration	Integrates components of the product.
Milestone	Used for showcasing progress.
Evaluation-*What evaluations are being performed?*	
Form	Evaluates the aesthetics of the product.
Fit	Evaluates how the components fit together.
Function	Evaluates the functionality of the prototype.
Manufacturing-*How was this prototype made?*	
Production Level	Manufactured as intended for the final product.
Outsourced	Manufactured by an outside source.
In-House	Manufacture in-house.
Scale-*What are the proportions of this prototype?*	
Full-Scale	Intended size of the final product.
To-Scale	Not intended for final product, but built to-scale of final.
Rough Scale	Similar to the scale of final product (within 20%).
Not-to-Scale	Built without regard to scale.
Functionality-*What functions does this prototype possess?*	
Fully Functional	Has all of the functions intended in the final product.
Partially	Has some functions intended for the final product.
Non-Functional	Is not functional/Appearance-only Model.
Components-*What components does this prototype include?*	
All	Includes all components intended in the final product.
Multiple	Includes multiple components.
Single	Is only of one component of the final product.

to possess the same mental model of how the product will look and/or function (Viswanathan, Atilola et al. 2014). The Functional category describes prototype that carry out some or all of the functions intended to be performed by the final product. The Integration category describes prototypes that combine separately developed components or design ideas to investigate how they perform as a whole system (Michaelraj 2009). Milestone prototypes are used for presentations or to benchmark a certain level of functionality (Ulrich and Eppinger 2004).

The next section defines the evaluations intended to be performed on the prototype. Eggert (2005) suggests that all prototypes can be grouped into one of three categories: Form, Fit, or Function. Form evaluations are used to determine if the product has an acceptable appearance. Fit evaluations determine how well the separate parts fit together properly and if the product fits well in the space it is intended for. Function evaluations test how well the product completes its desired functions. The designers were also asked to list the Function evaluations that were performed on each prototype.

The Manufacturing section defines how the prototype is created. The prototype may be made in-house by the designer or outsourced. Depending on the nature of the product being developed, the final prototype may be made at a separate facility to test the production level on a mass quantity level. Prototypes made using the intended production method enable the evaluation of the design’s compatibility with the intended manufacturing method (Pei, Campbell, and Evans 2011). The designers also described what materials were used to create each prototype and whether or not these materials differed from the intended production material.

The Scale section defines the size of the prototype compared to the intended production size. Otto and Wood (2001) state that prototypes can be to-scale, large-scale, or small-scale. The classification system developed for this study allowed more specific options of a to-scale model or not-to-scale prototype. A rough scale model was also included as an option to classify models made nearly to scale, but no scale measurements were actually considered.

The Functionality section looks to define the level of functionality of the prototype. Otto and Wood (2001) present useful ways to divide the functions of a product and discuss how each function can be improved individually. Therefore, not all prototypes are fully functional. That is, some prototypes are created only to address how one or some of the functions is address by the overall product. These prototypes are categorized as being partially functional while prototypes that address all of the intended functions are classified as fully functional prototypes. A prototype can also be non-functional, not possessing any functionality and created solely to represent the aesthetics of the final product.

The final section defines how any components are included in the prototype. Moe, Jensen, and Wood (2004) discuss the benefits of prototyping separate parts of a product to reduce fixation along with other benefits. By creating a “less complete” prototype that omits component to be included in the final product, the prototype can be used to more fully evaluate the effectiveness of each individual component. This section classifies prototypes as either single component, including multiple components, or including all components intended to be included in the final product.

In previous efforts to create a prototyping taxonomy, orthogonality was considered to be a measure of success between the categories in each section (Michaelraj 2009, Pei, Campbell, and Evans 2011). However, the authors of this paper found it more appropriate to allow the designer to choose all categories that applied to a prototype for the Purpose and Evaluation sections as this created a more accurate description of why the prototype was constructed.

It is important to note that this study used the presented categorization system to gather data. This allowed us to have a clear definition of why the prototype was constructed in the opinion of the designers and provided a tool with which to construct the interviews around. Future studies may be done to evaluate the strength of this classification system, but that is not the scope of the current study.

A.2.3 SIMPLE BoS

The study described in this paper is conducted on a project carried out by Georgia Tech Research Institute (GTRI) aiming to minimize the balance of system (BoS) costs associated with the production of solar energy. The BoS typically consists of mounting of solar panels and power-conditioning equipment to properly convert the generated DC to AC. They may also contain batteries for operation on cloudy days. Currently, BoS costs account for around 40% of the total installed cost of the solar energy systems.

The SunShot Initiative by the U.S. Department of Energy (DOE) aims to produce cost effective solar energy. This program aims to reduce the cost of solar energy production by 75% before 2020 (Camburn, et al. 2015). As a part of achieving this target, the DOE provided a grant to the researchers at the Georgia Institute of Technology to develop commercially-ready, next generation solar PV BoS designs (Dunlap, et al. 2014). This project, titled “SIMPLE BoS” (Solar, Installation, Mounting, Production, Labor and Equipment), is led by the Georgia Tech Research Institute (GTRI). The final goal of the SIMPLE BoS project is to reduce the racking/mounting hardware and labor costs by greater than 50%.

As a part of this project, the team involved produced many prototypes at each stage. For example, Figure A1 shows an early stage mock-up of the supporting structure design during its design phase. Figure A2 shows a fully functional system on the rooftop of a commercial building. This design was a result of the team’s extensive design and prototyping process. Many times, these prototypes provide them useful insights and inspire significant changes in their ideas. As the team consists of experienced professional designers, this project provides an ideal opportunity to learn about the benefits of prototyping for professional designers.

Figure A1. Residential Mockup Developed during Early-Phase Design

Figure A2. Installed, Fully-Functional System on the Rooftop of Install

A.2.4 Framework

Extensive prior by Camburn, et al. (2015), has identified a set of decisions designs must make when defining a prototyping strategy. This serves as one of the theoretical frameworks for this research guiding the type of data that is gathered. Camburn, et al. (2015) outlines the following set of 'strategy variables':

- *Parallel versus serial concept prototyping-* Design team may intentionally prototype multiple completely different design concepts simultaneously. Alternatively a single design concept may be chosen and only one concept is prototyped at a time.

- *Planned iterations*- Depending on the available time, design risk, and costs of individual prototypes, team may intend to create multiple iterations of a design or may plan for only very few.

- *Scaling*- Prototypes can be a different size than the actual size. Micro or smaller scale components may be scaled up to macro size. Large objects such as buildings and airplanes are often scaled down.

- *Subsystem isolation*- Only subsystem or partial systems may be prototyped. The design may be optimized and improved at the component level.

- *Design Requirement Relaxation*- Prototypes may performance at a lower level than required by the final design. For example, they may have lower strength, less corrosion resistance, able to withstand fewer cycles.

- *Physical vs Virtual*- The virtual prototyping can model a wide range of product performance parameters. Some virtual prototyping is extremely fast and efficient while other times physical prototypes provide either more accurate data or are simply faster and cheaper to build.

The systematic, empirical study of prototyping practices is an emerging area in design research and warrants much greater study. This paper seeks to add to this growing body of literature by providing an in-depth analysis of the prototyping process for a highly innovative team of designers.

A.3 Research Methodology

The research question sought to be answered through the study of the expert designers is: *What strategies are used by expert designers in the construction, implementation, and evaluation of prototypes to aid in the development of a final product?* The SIMPLE BoS project is an excellent opportunity to answer this question due to the number and variety of physical prototypes used during the design process. This study lends itself to more qualitative methods as it looks specifically at why something occurs and the impacts of certain design decisions (Borrego, Douglas, and Amelink 2009). A qualitative study such as this one can provide a deeper insight into the motivations of the designers and how the project looks from their point-of-view (Daly, McGowan, and Papalambros 2013). This insight allows for a more complete understanding of the strategies implemented by the designers. The semi-structured interviews of the designers with the use of the prototype classifications developed by the authors allow for an effective way for this data to be collected.

A.3.1 Semi-structured Interview

The data in this study was collected through three semi-structured interviews with a lead designer on one of the SIMPLE BoS teams who was also a student pursuing his PhD in architecture. These interviews lasted about one hour each and were conducted by the first author. For the first two meetings, the second author was present and assisted in the interview by asking follow-up questions. Both interviewers collected data via pen and paper. After the first interview, a slightly modified list of classifications was created. This classification list was a simplified version of the original list, leaving off categories originally included that remained constant throughout all of the prototypes. For example, all of the prototypes were made to-scale. Therefore, after the first interview, the scale classification was left off the list. This allowed the interviewers to focus more on the aspects that were changing between the prototypes. The data collected from this interview was aimed to gain a more in-depth understanding of the data collected in a previous study by Viswanathan, Atilola et al. (2014) by using this qualitative approach. The designer was provided with a copy of the classification list along with pictures of prototypes collected from the previous study. These prototypes were developed during various stages of the design process. The designer was asked to use the classifications provided to describe each prototype. The classification system provided structure to the interview to be based around, but open discussion about each prototype was had with emphasis on the reasoning behind the purpose of the creation of each prototype, at what point in the design process they were created, and what was learned from the evaluations. The designer was also able to list which evaluations were performed on each prototype.

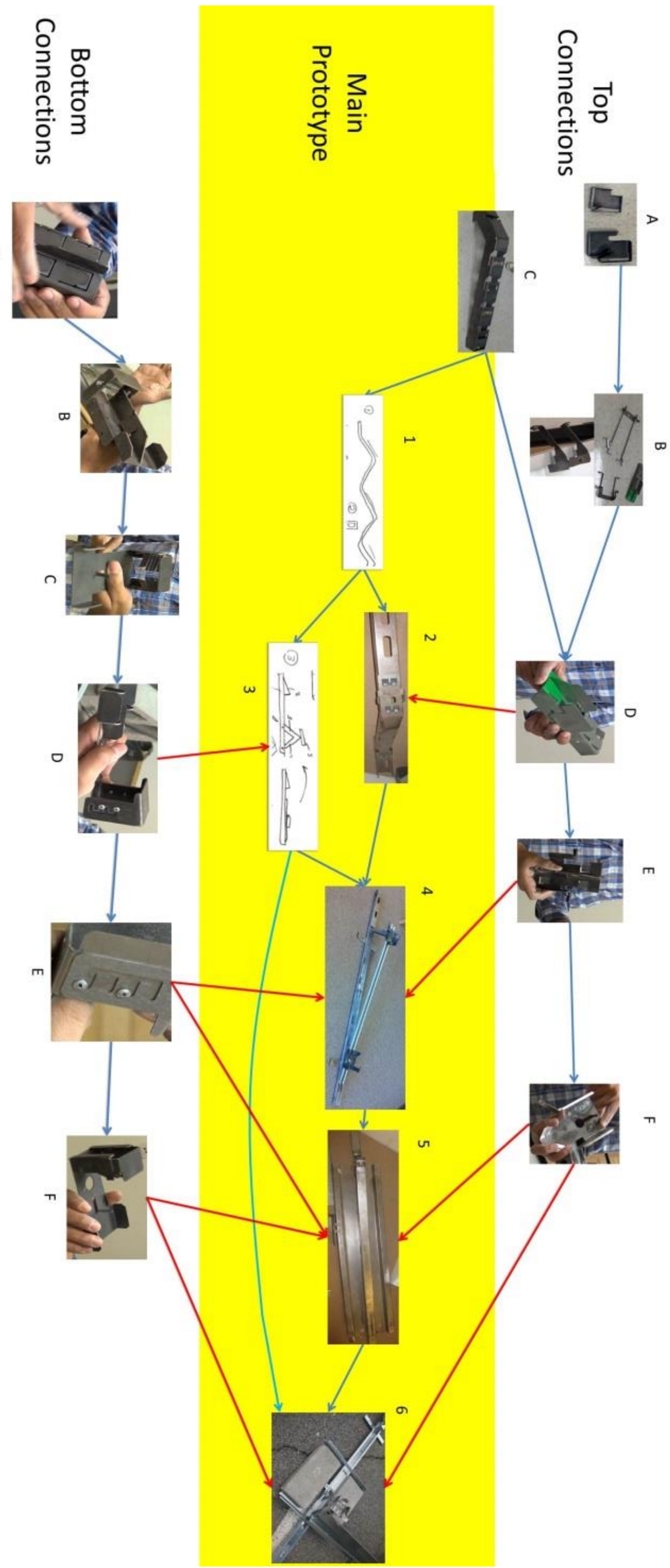


Figure A3. Overview of Prototypes. Prototypes are shown in chronological order with indicators showing influence from previous versions.

A.4 Findings

Table A2: Total Number of Each Classification			
Classification	Total	Complete Prototype	Component Prototype
Purpose			
Design Intent	19	6	13
Functional	19	6	13
Integration	19	6	13
Milestone	3	3	0
Evaluation			
Form	19	6	13
Fit	19	6	13
Function	19	6	13
Manufacturing			
Final Production Level	0	0	0
Outsourced	0	0	0
In-House	19	6	13
Scale			
Intended Production	19	6	13
To-Scale	0	0	0
Rough Scale	0	0	0
Not-to-Scale	0	0	0
Functionality			
Fully Functional	13	1	12
Partially Functional	5	5	0
Non-Functional	0	0	0
Components			
All components	6	6	0
Multiple components	0	0	0
Single Component	13	0	13

The results of the interviews are summarized in Table A2 and Figure A3. Through analysis of the data collected in this study, three major findings arose answering the question, "What strategies are used by expert designers in the construction, implementation, and evaluation of prototypes to aid in the development of a final product?" The first finding was that the designers would begin each iteration of a design on the component level. The second finding was that the designers would revert back to previous version of a design if they reached a point in their design reached a local maximum. The third finding showed that the designers would continually build upon the list of evaluations they would perform on each prototype in both number and level of sophistication.

The designers on the SIMPLE BoS project were intent on being able to develop each component of the overall product separately. The team would then combine all of the components to test the entire prototype and determine how it could be improved upon. However, instead of trying to improve the entire prototype, they would focus on the separate components. This can be seen in Figure A3**Error! Reference source not found.** as the connection components that attached to the top of the solar panel were developed simultaneously with the connection at the bottom of the solar panel, and both connection components were continuously being improved upon as the overall design advanced.

A.4.1 Iterative Design Process on the Component Level

Through an iterative process the designers would build, test, and evaluate a single component prototype until it reached the level desired to be implemented with the other components. Once all the separate components met this desired standard, the entire prototype would then be tested with all the components. Based on those evaluations, it would be determined what design changes need to take place to the overall prototype which determined what adjustments needed to be made on the component level. The process would then begin again with a testing and evaluating each component. This process can be visualized as a flow chart as seen in Figure A4**Error! Reference source not found.**.

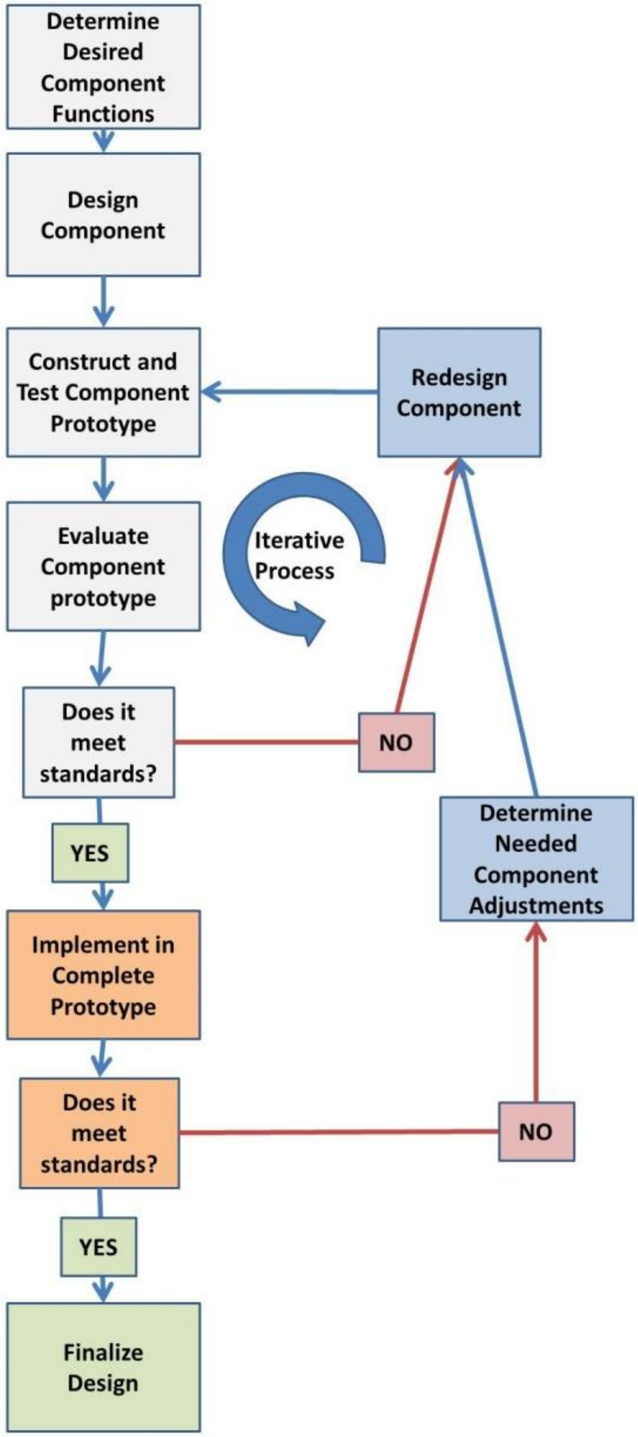


Figure A4. Iteration Design Process Implemented by the Design Team

This process was utilized to reduce the costs of prototypes as it was typically far less expensive to build and test a single component than to test an entire system. Therefore, the designers would want to ensure each component was designed properly before putting in the time and money into constructing and testing the full system.

Previous research has shown the effectiveness of iteration of prototypes in the design process (Christie, et al. 2012). It allows for an optimization of design and is effective at overcoming difficult requirements. Dividing the prototype and designing components separately as was done in this project also allows for an effective optimization and products of a higher quality (Moe, Jensen, and Wood 2004).

A.4.2 Strategic Backtracking

Whenever the design team found they had reached a local maximum in their design, they would often revert back to previous designs to determine what decisions were made to get them to their current state. They would then "backtrack" to a point of a major decision and then make the opposite one to see if that difference would help them to overcome that locally optimized design in search of a more globally optimized design.

The best example of this led to the final overall design of the system. A local maximum was reached near the end of the design process. The design would have been acceptable, except they were forced to change certain aspects of the structure due to a conflicting Intellectual Property. Therefore, they had to backtrack to a previous decision that lead them to the conflicting IP and find a different approach. When they reexamined a design a few iterations back, they discovered that they were able to combine aspects of their current design with aspects of that previous one and create a more optimized final design that also avoided the IP conflict (Figure A5).

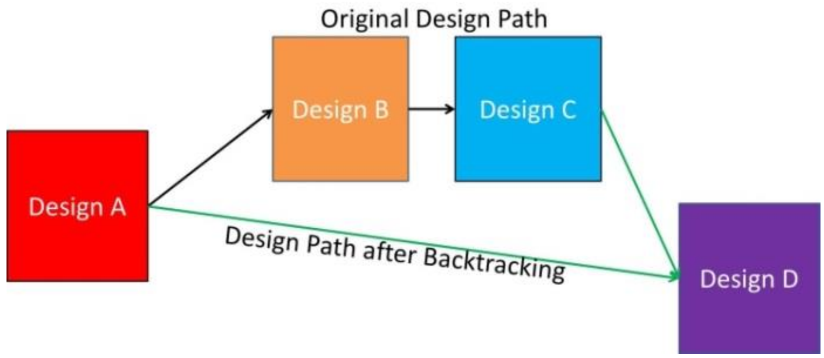


Figure A5. Backtracking Flow Chart

A.4.3 Growing Evaluation Lists

The final major finding gathered from the data was the evolution of the evaluations. During the early stages of the design process, most of the evaluations were quick and easy tests. For example, the early prototypes were statically tested by loading the panels down with sandbags so see how much weight that could hold. By the end of the end of the design process, the designers were utilizing much more formal tests such as using loading machines to evaluate the structural integrity.

Not only did the tests become more formal, as they progressed through the design process, the number of different evaluations steadily grew. As they evaluated each prototype, more tests were added to determine how effective their design was becoming. Every time a new test was performed, that test would be performed on every prototype evaluated thereafter. A prime example of this was a test the design team referred to as the “step on” test. During one of the evaluations of the complete prototype system, one of the designers noticed a section the frame that was not designed to hold weight looked rather fragile. To simulate a worker installing the panels, he stepped on that section of the frame to hoist himself to the opposite side. The section of frame was broken as a result and the designers quickly realized the adjustments that needed to be made to account for unanticipated loads during installation. After that evaluation, every complete prototype was tested by having a worker step on it as a worker may in the installation process.

By continuing to improve their evaluation methods, the designers were able to more confidently state that the final prototype was up to the standard that was desired. The final design was put through a complete set of formal tests including static loading, electrical grounding, packing space needed, ease of assembly, and the "step on test".

A.5 Conclusion

The study of highly successful professional design teams has great potential to provide guidance on effective strategies for the design and prototyping process. Data collection on practicing designers can be extremely challenging due to intellectual property issues, the long-time spans of projects, large amounts of data and many other issues. This paper presents a study of the prototyping process for a multi-million dollar, very successful, department of energy project. A targeted approach collects data on the prototyping practices.

This paper first presented a prototype classification approach based on an extensive literature review and then used the prototype classification to provide insights into the team's prototyping process. Data collection was targeted at the prototyping process using structured interviews. This design team only implemented full-scale (production scale) prototypes that had the design's final intended form, fit and function. This paper only illustrates one of the three designs that this team worked on and all designs contained a relatively high number of full-scale prototypes. This strategy choice may be significantly impacted by the type of product being designed and the team's goals. The goals were centered on installation cost reductions, a characteristic that is difficult to predict without a physical prototype at full-scale or very detailed mental models due to extensive experience in installing solar panels. For very innovative designs it can also be very difficult to make accurate predictions based on a person's mental models.

This team also implemented a very extensive number of component level prototypes illustrating the need for students to be very effective at recognizing system interfaces, key functions of components, the ability to optimize at the component level, and the knowledge to easily switch between component and system level thinking. All of the prototypes in this paper were built in-house likely due to the fact that these designs contain standard machining processes and the universities extensive prototyping resources were available. This often led to design ideas that could be more quickly evaluated. This may have also biased the team towards designs that could be quickly built in-house. However, one of the main goals of the design was to create a system that could be mass-manufactured using low-cost methods. These methods include process such as stamping and roll-forming which were replicable to a large degree due to the experienced fabricators available in-house to the design team. Therefore, these in-house designs are still viable representations of their mass-manufactured versions.

The data presented in this paper is one of three designs sought by the team. Interviews of with the designers for the other two prototypes are still in progress and will provide more details on the prototyping process for the team.

Effective prototyping skills and strategies are just one of the many tools engineers need to be highly effective engineers. More work needs to be done on developing prototyping strategies and best practices in utilizing prototypes in the design process.

APPENDIX B. LONGITUDNIAL DATA TABLES

B.1 Demographic Data from University C

Table B1. University C Longitudinal Demographic EDSE Data: Freshman Pre-course

Demographic	n	Average	t	df	p	d
Confidence						
Female	359	42.14	5.09	1559	<0.001‡	0.303
Male	1202	50.42				
URM	271	49.48	0.655	1560	0.513	0.040
non-URM	1291	48.28				
1st Gen	246	51.06	1.63	1558	0.104	0.110
non-1st Gen	1314	47.95				
Motivation						
Female	359	75.68	1.87	1559	0.061*	0.110
Male	1202	77.95				
URM	271	79.96	2.32	1560	0.021†	0.155
non-URM	1291	76.86				
1st Gen	246	77.07	0.281	1558	0.779	0.020
non-1st Gen	1314	77.47				
Expectation of Success						
Female	359	50.36	3.56	1559	<0.001‡	0.221
Male	1202	56.08				
URM	271	56.05	0.866	1560	0.386	0.058
non-URM	1291	54.50				
1st Gen	246	58.58	2.47	1558	0.014†	0.171
non-1st Gen	1314	54.00				
Anxiety						
Female	359	53.43	6.92	1559	<0.001‡	0.416
Male	1202	41.64				
URM	271	46.24	1.15	1560	0.249	0.077
non-URM	1291	44.02				
1st Gen	246	48.98	2.70	1558	0.0069‡	0.188
non-1st Gen	1314	43.59				

*Significant at α=0.10, †Significant at α=0.05, ‡Significant at α=0.01
d>0.2 is considered small effect, d>0.5 is considered medium effect, and d>0.8 is considered large effect(Cohen 1988)

Table B2. University C Longitudinal Demographic EDSE Data: Freshman Post-course

Confidence						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	391	73.15	4.23	1713	<0.001‡	0.244
Male	1324	77.24				
URM	297	78.11	2.02	1716	0.044†	0.129
non-URM	1421	75.93				
1st Gen	219	76.03	0.385	1384	0.700	0.020
non-1st Gen	1167	76.50				
Motivation						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	391	77.60	2.63	1713	0.0087‡	0.151
Male	1324	81.74				
URM	297	83.06	1.61	1716	0.107	0.103
non-URM	1421	80.24				
1st Gen	219	81.05	0.134	1384	0.894	0.010
non-1st Gen	1167	80.76				
Expectation of Success						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	391	72.33	3.79	1713	<0.001‡	0.218
Male	1324	76.23				
URM	297	75.69	0.360	1716	0.719	0.022
non-URM	1421	75.28				
1st Gen	219	74.79	0.619	1384	0.536	0.046
non-1st Gen	1167	75.60				
Anxiety						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	391	43.96	4.79	1713	<0.001‡	0.276
Male	1324	36.13				
URM	297	40.88	1.97	1716	0.0487†	0.126
non-URM	1421	37.28				
1st Gen	219	42.79	3.35	1384	<0.001‡	0.246
non-1st Gen	1167	35.84				

*Significant at α=0.10, †Significant at α=0.05, ‡Significant at α=0.01
d>0.2 is considered small effect, d>0.5 is considered medium effect, and d>0.8 is considered large effect(Cohen 1988)

Table B3. University C Longitudinal Demographic EDSE Data: Sophomore

Confidence						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	86	66.86	1.41	347	0.156	0.175
Male	263	70.04				
URM	64	72.03	1.379	347	0.171	0.190
non-URM	286	68.60				
1st Gen	35	69.43	0.231	239	0.818	0.042
non-1st Gen	206	68.64				
Motivation						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	87	65.99	3.00	348	0.0029‡	0.371
Male	263	73.92				
URM	64	75.64	1.48	348	0.139	0.205
non-URM	286	71.22				
1st Gen	35	71.71	0.274	240	0.784	0.050
non-1st Gen	207	70.58				
Expectation of Success						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	87	65.38	1.38	347	0.168	0.171
Male	262	68.47				
URM	64	70.50	1.35	347	0.177	0.187
non-URM	285	67.11				
1st Gen	35	68.29	0.726	239	0.468	0.133
non-1st Gen	206	65.82				
Anxiety						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	87	36.89	2.49	346	0.013†	0.308
Male	261	28.35				
URM	63	26.75	1.167	346	0.244	0.162
non-URM	285	31.28				
1st Gen	35	28.57	0.184	239	0.854	0.034
non-1st Gen	206	29.51				

*Significant at α=0.10, †Significant at α=0.05, ‡Significant at α=0.01
d>0.2 is considered small effect, d>0.5 is considered medium effect, and d>0.8 is considered large effect(Cohen 1988)

Table B4. University C Longitudinal Demographic EDSE Data: Senior

Confidence						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	34	80.59	0.280	108	0.780	0.058
Male	76	79.61				
URM	16	83.75	0.981	108	0.329	0.265
non-URM	94	79.26				
1st Gen	14	75.00	0.973	84	0.333	0.284
non-1st Gen	72	80.14				
Motivation						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	34	78.53	0.354	108	0.724	0.073
Male	76	76.97				
URM	16	83.13	1.16	108	0.249	0.313
non-URM	94	76.49				
1st Gen	14	76.43	0.140	84	0.889	0.041
non-1st Gen	72	77.36				
Expectation of Success						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	33	81.52	1.07	107	0.287	0.223
Male	76	77.24				
URM	16	78.75	0.049	107	0.961	0.013
non-URM	93	78.49				
1st Gen	13	75.38	1.22	83	0.226	0.367
non-1st Gen	72	81.39				
Anxiety						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	33	36.36	0.477	96	0.635	0.102
Male	65	39.54				
URM	14	32.14	0.822	96	0.413	0.237
non-URM	84	39.52				
1st Gen	12	51.67	1.324	82	0.189	0.413
non-1st Gen	72	38.61				

*Significant at α=0.10, †Significant at α=0.05, ‡Significant at α=0.01
d>0.2 is considered small effect, d>0.5 is considered medium effect, and d>0.8 is considered large effect(Cohen 1988)

Table B5. University C Longitudinal Demographic GPA Data

Freshman GPA						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	83	3.43	0.585	207	0.559	0.083
Male	126	3.47				
URM	33	3.32	2.04	207	0.043†	0.387
non-URM	176	3.48				
1st Gen	12	3.43	0.266	105	0.791	0.081
non-1st Gen	95	3.47				
Sophomore GPA						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	47	3.32	1.40	158	0.164	0.266
Male	113	3.44				
URM	24	3.24	1.96	158	0.052*	0.518
non-URM	136	3.43				
1st Gen	7	3.43	Not analyzed due to the low number of 1st-Generation students.			
non-1st Gen	61	3.37				
Senior GPA						
Demographic	**n**	**Average**	**t**	**df**	**p**	**d**
Female	11	3.40	Not analyzed due to the low number of participants.			
Male	8	3.57				
URM	3	3.43	Not analyzed due to the low number of participants.			
non-URM	16	3.48				
1st Gen	3	3.90	Not analyzed due to the low number of participants.			
non-1st Gen	16	3.29				

*Significant at α=0.10, †Significant at α=0.05, ‡Significant at α=0.01
d>0.2 is considered small effect, d>0.5 is considered medium effect, and d>0.8 is considered large effect(Cohen 1988)

B.2 University B University Demographic Data

Table B6. University B Longitudinal Demographic EDSE Data: Freshman

Demographic	n	Average	t	df	p
Confidence					
Female	37	65.68	2.43	159	0.016†
Male	124	74.19			
URM	25	72.40	0.404	155	0.687
non-URM	132	71.97			
1st Gen	5	78.00			
non-1st Gen	68	70.15			
Motivation					
Female	37	77.03	1.21	159	0.229
Male	124	80.89			
URM	25	81.20	0.136	155	0.892
non-URM	132	79.77			
1st Gen	5	98.00			
non-1st Gen	68	78.24			
Expectation of Success					
Female	37	69.73	1.76	159	0.081*
Male	124	75.40			
URM	25	75.20	0.078	155	0.938
non-URM	132	73.79			
1st Gen	5	86.00			
non-1st Gen	68	73.68			
Anxiety					
Female	37	52.43	0.355	159	0.723
Male	124	50.56			
URM	25	57.20	1.38	155	0.170
non-URM	132	49.62			
1st Gen	5	28.00			
non-1st Gen	68	52.06			

*Significant at $\alpha=0.10$, †Significant at $\alpha=0.05$, ‡Significant at $\alpha=0.01$
d>0.2 is considered small effect, d>0.5 is considered medium effect, and d>0.8 is considered large effect(Cohen 1988)

Table B7. University B Longitudinal Demographic EDSE Data: Sophomore

Confidence					
Demographic	**n**	**Average**	**t**	**df**	**p**
Female	28	75.71	2.40	119	0.018†
Male	93	82.80			
URM	16	81.25	0.051	118	0.960
non-URM	104	81.06			
1st Gen	10	78.00	0.846	107	0.400
non-1st Gen	99	82.02			
Motivation					
Demographic	**n**	**Average**	**t**	**df**	**p**
Female	28	84.29	0.370	119	0.712
Male	93	85.48			
URM	16	86.88	0.464	118	0.644
non-URM	104	85.00			
1st Gen	10	82.00	0.780	107	0.437
non-1st Gen	99	85.86			
Expectation of Success					
Demographic	**n**	**Average**	**t**	**df**	**p**
Female	28	75.36	0.370	119	0.712
Male	93	80.65			
URM	16	84.38	1.677	118	0.096*
non-URM	104	78.46			
1st Gen	10	82.00	0.780	107	0.437
non-1st Gen	99	79.60			
Anxiety					
Demographic	**n**	**Average**	**t**	**df**	**p**
Female	28	46.79	0.666	119	0.506
Male	93	42.58			
URM	16	32.50	1.59	118	0.115
non-URM	104	44.81			
1st Gen	10	54.00	1.33	107	0.185
non-1st Gen	99	40.81			

*Significant at α=0.10, †Significant at α=0.05, ‡Significant at α=0.01
d>0.2 is considered small effect, d>0.5 is considered medium effect, and d>0.8 is considered large effect(Cohen 1988)

Table B8. University B Longitudinal Demographic EDSE Data: Junior

Confidence					
Demographic	**n**	**Average**	**t**	**df**	**p**
Female	22	87.27	0.594	90	0.554
Male	70	85.57			
URM	11	86.36	0.129	89	0.898
non-URM	80	85.88			
1st Gen	13	86.92	0.181	89	0.857
non-1st Gen	78	86.28			
Motivation					
Demographic	**n**	**Average**	**t**	**df**	**p**
Female	22	82.73	0.554	90	0.581
Male	70	80.43			
URM	11	77.27	0.772	89	0.442
non-URM	80	81.50			
1st Gen	13	82.31	0.199	89	0.857
non-1st Gen	78	81.28			
Expectation of Success					
Demographic	**n**	**Average**	**t**	**df**	**p**
Female	22	85.00	0.953	90	0.343
Male	70	82.14			
URM	11	86.36	1.01	89	0.317
non-URM	80	82.38			
1st Gen	13	80.77	0.199	89	0.843
non-1st Gen	78	83.46			
Anxiety					
Demographic	**n**	**Average**	**t**	**df**	**p**
Female	22	35.91	0.527	89	0.599
Male	69	32.17			
URM	11	28.18	0.574	88	0.567
non-URM	79	33.54			
1st Gen	13	34.62	0.736	89	0.463
non-1st Gen	77	32.86			

*Significant at α=0.10, †Significant at α=0.05, ‡Significant at α=0.01
d>0.2 is considered small effect, d>0.5 is considered medium effect, and
d>0.8 is considered large effect(Cohen 1988)

Table B9. University B Longitudinal Demographic EDSE Data: Senior

Confidence					
Demographic	**n**	**Average**	**t**	**df**	**p**
Female	11	89.09	0.906	51	0.369
Male	29	92.07			
URM	6	86.67			
non-URM	33	92.42			
1st Gen	6	96.67			
non-1st Gen	35	90.57			
Motivation					
Demographic	**n**	**Average**	**t**	**df**	**p**
Female	11	87.27	0.236	51	0.815
Male	29	86.90			
URM	6	85.00			
non-URM	33	87.88			
1st Gen	6	93.33			
non-1st Gen	35	86.00			
Expectation of Success					
Demographic	**n**	**Average**	**t**	**df**	**p**
Female	11	87.27	0.415	51	0.680
Male	29	86.90			
URM	6	85.00			
non-URM	33	87.27			
1st Gen	6	88.33			
non-1st Gen	35	86.57			
Anxiety					
Demographic	**n**	**Average**	**t**	**df**	**p**
Female	11	21.82	0.614	51	0.542
Male	29	21.38			
URM	6	15.00			
non-URM	33	23.33			
1st Gen	6	15.00			
non-1st Gen	35	22.29			

*Significant at α=0.10, †Significant at α=0.05, ‡Significant at α=0.01
d>0.2 is considered small effect, d>0.5 is considered medium effect, and d>0.8 is considered large effect(Cohen 1988)

Table B10. University B Longitudinal Demographic GPA Data

Freshman					
Demographic	**n**	**Average**	**t**	**df**	**p**
Female	35	2.82	1.62	151	0.107
Male	119	2.63			
URM	24	2.51	1.35	147	0.179
non-URM	126	2.71			
1st Gen	5	2.84	Not analyzed due to low number of 1st-Generation participants		
non-1st Gen	73	3.02			
Sophomore					
Demographic	**n**	**Average**	**t**	**df**	**p**
Female	21	2.86	0.217	81	0.829
Male	63	2.83			
URM	13	2.72	1.08	81	0.282
non-URM	71	2.86			
1st Gen	8	2.84	Not analyzed due to low number of 1st-Generation participants		
non-1st Gen	75	2.84			
Junior					
Demographic	**n**	**Average**	**t**	**df**	**p**
Female	23	3.04	0.665	92	0.507
Male	71	2.98			
URM	11	2.91	0.851	91	0.397
non-URM	82	3.00			
1st Gen	13	2.97	0.386	90	0.700
non-1st Gen	79	3.01			
Senior					
Demographic	**n**	**Average**	**t**	**df**	**p**
Female	11	3.22	1.62	53	0.109
Male	30	3.05			
URM	6	3.15	Not analyzed due to low number of Under-Represented participants		
non-URM	34	3.08			
1st Gen	6	3.02	Not analyzed due to low number of 1st-Generation participants		
non-1st Gen	36	3.12			

*Significant at α=0.10, †Significant at α=0.05, ‡Significant at α=0.01
d>0.2 is considered small effect, d>0.5 is considered medium effect, and d>0.8 is considered large effect(Cohen 1988)

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